Ingénierie des Systèmes d'Information
Vol. 27, No. 6, December, 2022, pp. 895-902
Journal homepage: http://iieta.org/journals/isi

A Systematic Literature Review on Recommender Systems for MOOCs

Kawtar Najmani[1*], El Habib Benlahmar[1], Nawal Sael[1], Ahmed Zellou[2]

[1] Laboratory Information Technology and Modeling, Faculty of Sciences Ben M'sik, Hassan II University, Casablanca 20670, Morocco
[2] Laboratory Software Project Management, Mohammed V University in Rabat, ENSIAS, Rabat 10112, Morocco

Corresponding Author Email: kawtarnajmani@gmail.com

https://doi.org/10.18280/isi.270605

Received: 10 October 2022
Accepted: 30 November 2022

Keywords:
recommender system (RS), MOOCs, massive open online course, systematic literature review, course recommendation

ABSTRACT

In recent years, MOOCs (Massive Open Online Courses) have become popular and the online learning resources are increasing, they are an offered courses by schools and universities, which are accessible to everyone and free of charge on the internet, they offer the possibility to teach a very group of students, in the same course, at the same time, even if they are not in the same location. There are many MOOCs platforms with different characteristics, they contain a huge amount of data, so the learner does not know which course to take and can choose irrelevant MOOCs. Therefore, he will waste the time and also the motivation. Recommender systems give a solution to this problem, they suggest learning resources to learners according to their interests and needs, so learner will be satisfied because he finds an appropriate course. In this paper, we give a systematic literature review of MOOCs recommender systems, based on published papers in the past ten years, between 2012 and 2022. We have selected 123 papers from five databases, IEEE Xplore, Springer Link, Science Direct, Google Scholar and ACM Library. We have divided the data analysis in two parts, the quantitative analysis, and the qualitative analysis. In the quantitative analysis, we have studied first the evolution of papers by year and the distribution of papers on databases by type. Then, in the qualitative analysis, we have based principally on the distribution of papers by the existed areas in MOOCs. We have found that there are six main fields, course recommendation, peer recommender, MOOC provider, video recommendation, learning activities and OER, paid activities recommender system and other papers in various types. A high number of articles have been published in the field of courses, which confirms that this domain is very important and crucial for learners.

1. INTRODUCTION

The term "Massive Open Online Course" was first introduced in 2008 by Dave Cormier to describe George Siemens and Stephen Downes' CCK08 online course [1]. MOOCs is a free and open-access university-level courses that anyone and anywhere can register for these courses which are delivered over the internet. They can widen access to higher education for millions of people, so student can access complete offered courses. There are many MOOC platforms among them, Coursera, Udemy, Udacity and Edx. MOOCs have many advantages, they are free, and no tuition fees required. In addition, the courses are open to all interested even the location is different, so students can collaborate with their peers from different parts of the world. However, they have also some disadvantages. The training offered can be impersonal due to the lack of interaction. On the one hand, the student does not have supervision and personalized follow-up throughout the training. On the other hand, MOOCs tend to suppress social interactions between students. Moreover, the student is often confronted with the problem of a lack of motivation. The learning effort he must provide is greater because he must mobilize all his attention and not be diverted by any source of distraction.

The method used in courses differs significantly between platforms. In Udacity for example, the courses are always open. Those of Coursera have a beginning and an end. It is not always possible to consult the archives of a course once it has been completed. The pedagogy that underlies them vary a lot. While some teachers favor the lecture, others focus on the exercises and on the interaction between the students. Even if, there is a difference in the method of proposition of courses, MOOCs platforms share three characteristics. They are open, the registration procedures are very flexible. Then, they are massive, the number of registrants can vary from several hundred to several thousands of students. Finally, they rely heavily on exchanges between peers to provide support.

With the rapid development of MOOCs platforms, the online learning resources are increasing, and they contain a huge amount of data, so the user does not know which course can follow, for that we need recommender systems for MOOCs to help learners to choose an adequate and relevant course from several suggested courses. Recommender systems are based on two notions, items, which are the element that we recommend, and the second notion is user, it is to whom we will recommend the item. In order to give a recommendation, it is important to have a description of the item that we will recommend, moreover, we need to make a representation of user behaviors to know him better and give him relevant recommendations, this identification depends on the type of used approach. These systems propose to the user items that can interest him, they offer useful information adapted to users' profiles based on their preferences and behaviors, and they aim also to help users discover relevant products among several articles suggested because of the large volume of information, so in this case the user reduces the search time and find a good result.

There are principally three approaches that are used in the recommender systems like shown in Figure 1. First, content-based filtering which is based on the description of the item [2], so it assumes that the user will buy products which are similar to the products that they have bought. Second, we have collaborative filtering which is becoming diversified beacause there is a deep research in this field [3], it is based on user profile, it’s not interesting with the content of the element like content-based filtering. Its main goal is to offer to the current user the elements that are relevant to the users who are close to him. This technique is divided into two types, memory-based approach which is also divided into user-based and item-based [4], and model-based approach, the model building process is performed by these algorithms: clustering techniques, association rule, neural network, and Bayesian network. Third, hybrid filtering, it is a combination between two or more of recommendation techniques, so instead of using several techniques we can use just one.

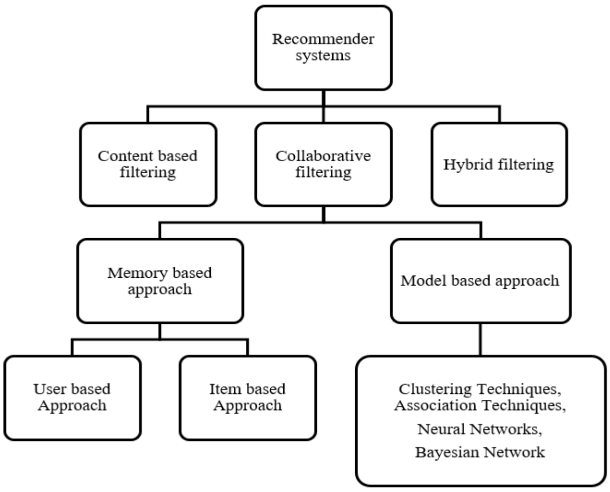

Figure 1. Recommender systems approaches

This paper is organized as follows. In section 2, we present our Systematic Literature Review method, this part contains the research questions, the databases that we have used to extract the relevant paper of our research, the research period, the keywords used in the search, and finally the data selection. Section 3 contains data analysis and results, it is divided in two main parts. The first one is the quantitative analysis, which contains the evolution of papers by year from 2012 to 2022 and the distribution of papers by publication type (conference papers, journal articles and book chapters). The second one is the qualitative analysis which analyzes the published papers by the existing fields in MOOCs. Section 4 presents a discussion of found results. The final section contains the conclusion and the future directions.

2. SYSTEMATIC LITERATURE REVIEW METHOD

A Systematic Literature Review (SLR) method describes and summarizes the state of relevant scientific research on a research question or topic and the results of several studies. There are many reasons to perform a systematic literature review among them, to summarize the existing evidence concerning a technology. In addition to that, we need to identify any gaps in current research in order to suggest areas for further investigation [5].

Our methodology contains two fundamental steps the first one contains many parts which are, research questions, the used databases, the keywords that we have used on our search, and data selection. The second step is data analysis, it is divided in two parts, quantitative and qualitative analysis. Figure 2 shows the process of our systematic literature review.

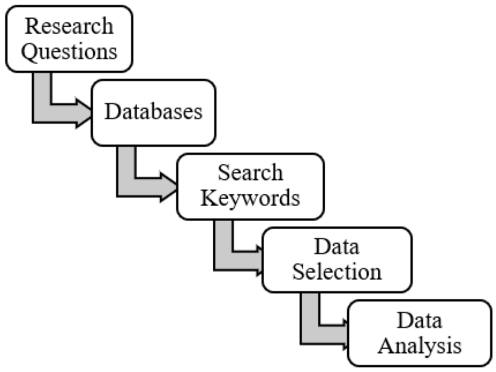

Figure 2. Flow of our systematic literature review method

The steps of the process flow of our systematic review method will be explained in the next sections.

2.1 Research questions

The reason for the need for a literature review is mandatory, here is the list of the research questions (RQ) of this paper:

RQ1. What is the evolution of research related to recommendation system for MOOCs from 2012 until 2022?

RQ2. What techniques are used to implement MOOC recommender systems in the papers?

RQ3. What are the areas of the implementation of MOOCs in recommender systems?

We have identified three RQ. RQ1 is defined to identify the evolution of research in MOOCs recommender systems in the last ten years. RQ2 is formulated to know the approaches that are used to implement MOOC recommender systems in published papers and solve existing problems in them. RQ3 is identified to have an idea about the fields which are very important for researchers and where they publish many papers.

2.2 Databases

The identification of the sources of research is a crucial step, it aims to collect many relevant research studies as possible, and which can help us to respond to our research questions. We have used five databases to identify the relevant papers that will help us to achieve our objectives: the Institute of Electrical and Electronics Engineers (IEEE) Xplore, Springer Link, Science Direct, Google Scholar and ACM Digital Library. Following the links to each one:

- IEEE Xplore (http://ieeexplore.ieee.org)
- Springer Link (https://link.springer.com)
- Science Direct (http://www.sciencedirect.com)
- Google Scholar (https://scholar.google.com)
- ACM Digital Library: (http://dl.acm.org)

2.3 Research period

We have reviewed the papers that have been published in the last 10 years, from 2012 to 2022.

2.4 Search keywords

Our review will be guided by the relevant following strings that we have selected in the search in the sources above by combining different keywords:

- **String 1:** (“MOOCs” OR “MOOC”) AND (“Recommender”, OR “Recommendation”, OR “Recommending”) AND (“System”, OR “Systems”)
- **String 2:** ((“Massive Open Online Courses (MOOCs)”) OR (“Massive Open Online Course (MOOC)”)) AND (“Recommender”, OR “Recommendation”, OR “Recommending”) AND (“System”, OR “Systems”)

2.5 Data selection

The inclusion and exclusion criteria must be carefully defined in order to give a good literature review, and to select only papers that are relevant to our search.

On the hand, conference papers, journals, and book chapters were included in this literature review. In addition, we have included just papers which are written in English language from 2012 to 2022, and the abstract or the title of the paper contains the keywords of the search. On the other hand, we do not take into consideration short studies, like summaries and poster, unpublished papers, paper which do not have a full pdf, paper which does not discuss MOOCs in recommender systems and returned in the search result, and we have excluded also articles which do not contain an experimental result (Table 1).

We have found 232 studies, after the application of the exclusion criteria we have selected only 123 papers.

Table 1. The criteria of the exclusion and the inclusion of the papers

Inclusion Criteria	Exclusion criteria
Papers written in English	Short articles like poster and summaries.
Papers published in conferences, journals, and book chapter	Unpublished papers
Papers published between 2012 and 2022	Articles which do not contain an experimental result.
The abstract or the title of the paper contains the keywords of the search	Full paper is unavailable
	The paper does not discuss MOOCs in recommender systems

3. DATA ANALYSIS AND RESULTS

Data analysis is divided in two main parts, the quantitative analysis, and the qualitative analysis.

3.1 Quantitative analysis

In the quantitative analysis, we have classified the evolution of papers by publication year, application domain, publication type, and finally by technique. To perform that, we have analyzed 123 papers that have been published in the last 10 years, between 2012 and 2022.

3.1.1 Evolution of papers by year

We studied the evolution of published papers on MOOCs recommender systems by year in order to have an idea about the evolution of this domain in the last ten years based on selected articles from all databases.

Figure 3 shows the number of papers published in each year from 2012 to 2022, we observed the fast evolution, which confirms the utility of this domain in recommendation systems. From 2012 to 2016 we observe a few published papers. After that, in 2017 an important and fast evolution appears and the number of papers increases as mentioned in the figure. From 2018 to June 2022 various papers are always published in this field which help to keep the evolution from 2017.

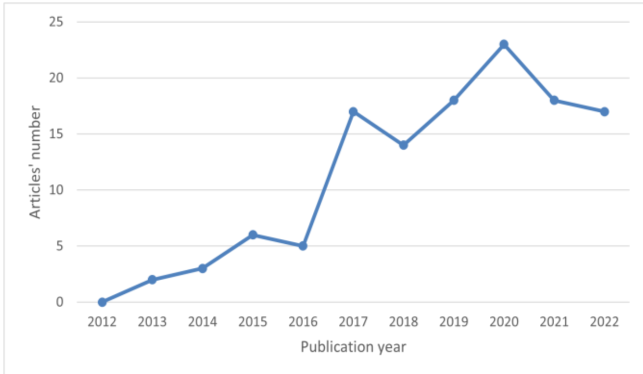

Figure 3. Evolution of moocs recommender systems papers by year from 2012 to 2022

3.1.2 Classification of papers by publication type

We have based on our systematic review on 123 papers distributed on several databases. Table 2 and Figure 4 shows the results found in the databases, we have based on 35 papers from IEEE Xplore, which composes 28% of total found results. Then, we have Springer link database, 29 papers and 24% of results used in this review. The ACM digital library is the third in the number of papers with 26 articles and a percentage of 21%. We also have Science Direct database with 18 papers and 15%. Finally there is Google Scholar source, we have used 15 papers and 12% of related articles.

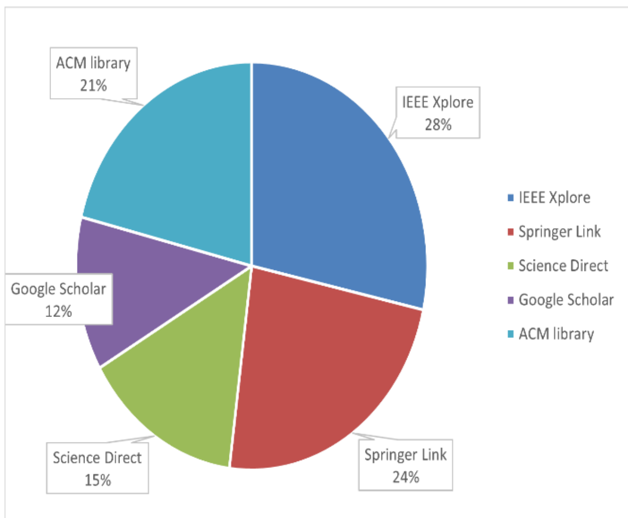

Figure 4. Distribution of papers found in databases

Table 2. The number of selected papers in each database

Database	Number of papers
IEEE Xplore	35
Springer Link	29
Science Direct	18
Google Scholar	15
ACM Library	26

In Figure 5, we present the distribution of different types of published papers that we are used in our research by year, from 2012 to 2022, we have based on 123 papers which contain three principal types, 79 of them are a conference papers, then 37 journal articles and 7 book chapters. As shown in the figure, there is no publication in 2012 related to MOOCs recommender systems, progressively we observe that the number of papers increased rapidly in the next few years.

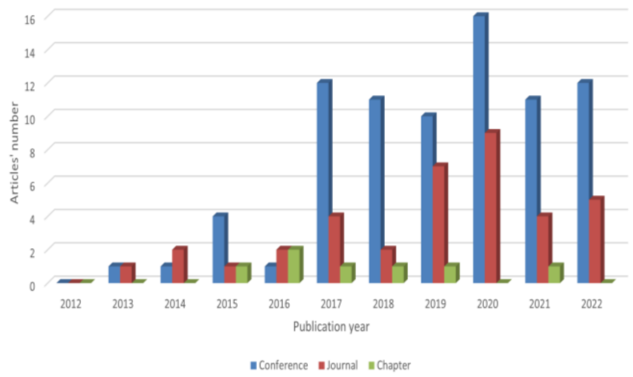

Figure 5. Distribution of papers by publication type

3.2 Qualitative analysis

In this part we will extract topics from papers and classify them.

Based on extracted papers, we have found that researchers analyze different topics on the application of MOOCs in recommender systems. The papers have been classified according to several fields of application, among them:

Course recommendation: The main task of MOOCs platforms is the recommendation of different courses to students, for that, many papers analyze this main topic to satisfy students and give them good and reliable recommendations.

Peer recommender: It consists of putting the student in the position of corrector by asking him to bring a critical eye and to note the work of other students (his peers). The large number of participants in MOOCs makes it strictly impossible for teachers to correct each production returned. Therefore, when automatic assessment is impossible, learners rate each other.

MOOC provider: It concerns the academic institutions that offer courses and recommendation of topics to them.

Video recommendation: In this area authors treat the recommendation of videos in a different way, they analyze suggested videos to give a recommendation better than the traditional way.

Learning activities and OER: This category contains papers related to OER and learning activities.

Paid activities recommender system: It concerns the act of helping learners to be paid for a task and have money while using MOOCs.

Other papers: papers which do not have a specific area exist in this part.

Figure 6 shows the distribution of papers that are published in MOOC recommender systems by categories. We have found that 56% of works is based on the category of course recommender, which is the high existing percentage, which confirms the importance of this field on the research of different authors. As a second one, we found video recommendation with 13%, the traditional way gives recommendation, but the authors found that the analysis and the treatment of videos gives more reliable results which enhance this category in MOOC recommender systems. Then, we have peer recommender, paid activities recommender system and learning activities and OER with 8%. Then, there is MOOC provider with 2%. We have also some published papers in other categories which contains just a few numbers of articles and present 5% of papers in our database.

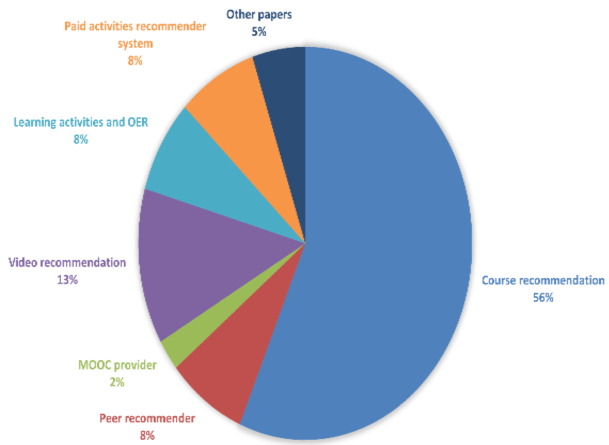

Figure 6. Distributiono of papers on existing categories in MOOC Recommender Systems

We have analyzed the found works, we have based on the Table 3 below which shows the distribution of papers by category per year in MOOC recommender systems.

Table 3. Distribution of some published papers by category in MOOC recommender systems per year

Research topic	Publication year	Related works
Course recommendation	2022	[6, 7]
	2019	[8, 9]
	2018	[10-12]
	2017	[13-19]
	2016	[20-22]
	2015	[23-26]
	2013	[27]
Peer recommender	2018	[28]
	2017	[29]
	2015	[30]
MOOC provider	2017	[31]
Video recommendation	2018	[32-36]
	2015	[37]
Learning activities and OER	2017	[38, 39]
Paid activities recommender system	2018	[40]
	2017	[41]
	2016	[42]
Other papers	2018	[43]
	2016	[44]
	2014	[45, 46]

4. DISCUSSION

We have many areas in MOOCs for recommender systems, which focus to the interest of this field in recommender systems. In our systematic literature review, we have reviewed the published papers in the last 10 years, from 2012 to 2022 in different databases. We have classified the papers that we have based in this review on six main categories, course recommendation, peer recommender, MOOC provider, video recommendation, learning activities and OER, paid activities recommender system and other papers in various types. In this part, we will discuss the types one by one, and the objective of researchers of published papers.

4.1 Course recommendation

Many researchers focus on the implementation of course recommendation because it can help in the improvement of the learning experience, and it is one of the challenges of MOOCs. Onah and Sinclair [26] analyze the application of MOOCs in recommender systems, especially in the category of course using collaborative filtering, Piao and Breslin [47] utilize content-based filtering algorithm. These two algorithms are very used in many papers, especially in the period between 2013 and 2016. Boratto et al. [9] analyze the effect of algorithmic bias, they compared the algorithms that already exist and the list that they recommend against biases related to catalog coverage, course popularity, and course category popularity. Some authors are based on new methods and frameworks, for example, Li and Li [18] presented a novel fusion recommender system for MOOCs, they propose a new metric to measure the relevance between user and courses based on the behavior of user in MOOCs platform, they also used the collaborative filtering algorithm. In addition, Fu et al. [25] proposed a new framework for designing an undergraduate-oriented recommendation system for MOOCs in which the particular characteristics of the participants like learning interest and learning motivation. Ouertani and Alawadh [20] presented a system which gives suitable courses among many providers, and it recommends courses related to the previous experiences of its users.

From 2017, the researchers started with the application of deep learning and neural networks in order to preprocess data and give recommendation [46-50]. Moreover, association rule mining is also introduced in [51], where authors present a new system which recommends learning resources, such as, relevant courses to learners, using a combination of association rules, collaborative filtering, and content-based filtering. Fauzan et al. [52] proposed a new system based on the apriori algorithm in association rule to recommend appropriate courses to learners in order to satisfy them.

4.2 Peer recommender

We have found same papers in the context of peer recommender systems which is also has an important role in MOOCs. Bouchet et al. [29] implemented a chat-based peer recommender systems which is used during a MOOC session to know the causes of the usage of peer communication in MOOCs, they found that students are not satisfied by the available othermeans of interactions, and they seem to use it more to share emotions than to learn together. In addition, Sunar et al. [30] proposed a new method for the measurement of the interactions and for predictions of interactions between peers, they found that if a learner interact with their peers, they will interact again in the next weeks. Reciprocal scores are also used in some papers, and they are the interest of some researchers [13], the objective is to give good recommendation of peers for learners.

4.3 MOOC provider

We take into consideration only one paper in this category [31], where authors implemented a new framework in order to give recommendation of courses to learners based on their curricular information by relying on their LinkedIn profiles, it has another objective which is the proposition of the topic which can interest MOOCs' providers based on the job market needs.

4.4 Video recommendation

Another category which researchers carried out on recommender systems for MOOCs is video recommendation to learners. Before, researchers do not analyze the content of videos to propose related videos to the topic of the same current video. Belarbi et al. [32] proposed a new approach in video recommender system in SPOC, which is based the algorithm K-means clustering to group users with similar video behavior into clusters and on the user's video clickstream to create the user profile. Moreover, researchers in [33-35] presented a system which gives recommendation of videos of courses. it takes into consideration the content of the video and sequential inter-topic relationships which are extracted from the syllabi of course. Furthermore, Bhatt et al. [36] presented a system of the recommendation of videos that combines sequential pattern mining of inter-topic relationships with topic-based video representation.

4.5 Learning activities and OER

Other researchers are based on their research on the field of learning activities and OER. On the hand, Harrathi et al. [38] presented a set of dimensions that describe learning activities, they give a proposition of the classification of the recommended learning activities based on Bloom's taxonomy, then they integrate them in a recommender system with modular architecture. On the other hand, Hajri et al. [39] proposed a new system to recommend OERs to MOOCs learners, it is based on learner profile, on a carefully crafted process and on metadata describing the course to query the SparQL endpoints for OERs.

4.6 Paid activities recommender system

While using MOOCs, another group of authors paid attention to help learners to have money, they will give some paid activities in recommender system by applying their skills. Harrathi et al. [38] proposed then implemented a system that recommend to learners courses which are related to paid tasks from online marketplaces, like Upwork or witmart. Consequently, the learners learn and earn money [39, 40].

4.7 Other papers

In this part, we categorize papers which do not have a particular field. A chatbot for MOOCs is proposed in [44] for Facebook Messenger, this system is based on the profile of users in social media and their interests. A recommender system based on threads is proposed in Yang et al. [45], it is presented in a discussion forum, it recommends questions for students and based on their knowledge they will answer. After that, Yang et al. [46] improved this system and make it less expensive in computation. Jain [43] focused on data mining techniques in order to propose a MOOC recommender system, they are based on the activity logs of learners to define if he is active or passive, they found 92% in average accuracy, if the user is active for the course recommendation.

5. CONCLUSION AND FUTURE WORK

In MOOCs platforms, data collected and stored in databases has grown considerably due to advances in software and hardware which led to the automation of data processing processes. Therefore, traditional management information systems techniques have become inappropriate and other new tools have appeared. Recommender systems are intended to assist learners during their learning process to remedy the massification of exchanged data between learners. They aim to help learners to find relevant information from an important amount of data.

In this paper, we have based on 123 papers that have published in the last decade, from 2012 to 2022, to present a systematic literature review of MOOCs recommender systems. We have found that recommender systems in MOOCs knows an evolution in the last ten years, especially from 2017. We have divided the fields which exist in published papers into six types, and we have found that many researchers paid attention and publish many papers in the area of course recommender which is one of the challenges of MOOCs.

Several researchers are working on MOOCs recommender systems, but the traditional systems do not use the clickstream analysis. This is the reason why in the future, we will propose a new recommender system in the field of MOOCs based on clickstream analysis, in order to detect the part, which attract more attention of the learner. On the other hand, it can help teachers to have an idea about the topic which interests the learner, so they can record other detailed videos on the same topic.

REFERENCES

[1] Duma, M., Twala, B. (2019). Sparseness reduction in collaborative filtering using a nearest neighbour artificial immune system with genetic algorithms. Expert Systems with Applications, 132: 110-125. https://doi.org/10.1016/j.eswa.2019.04.034

[2] Najmani, K., El habib, B., Sael, N., Zellou, A. (2019). A comparative study on recommender systems approaches. In Proceedings of the 4th International Conference on Big Data and Internet of Things, pp. 1-5. https://doi.org/10.1145/3372938.3372941

[3] An, Q.Q. (2019). A novel recommendation algorithm considering average similarity and user-based collaborative filtering. Mathematical Modelling of Engineering Problems, 6(3): 390-396. https://doi.org/10.18280/mmep.060310

[4] McAuley, A., Stewart, B., Siemens, G., Cormier, D. (2010). The MOOC model for digital practice. Scientific Research, University of Prince Edward Island.

[5] Kitchenham, B. (2004). Procedures for performing systematic reviews. Keele, UK, Keele University, 33(2004): 1-26.

[6] Havas, S., Imanian, N., Moradi, P. (2022). A courses recommendation system based on graph clustering and ant colony optimization in MOOC environment. In 2022 9th International and the 15th National Conference on E-Learning and E-Teaching (ICeLeT), pp. 1-7. https://doi.org/10.1109/ICeLeT55619.2022.9765436

[7] Ahmad, H.K., Qi, C., Wu, Z., Muhammad, B.A. (2022). ABiNE-CRS: Course recommender system in online education using attributed bipartite network embedding. Applied Intelligence, 1-20. https://doi.org/10.1007/s10489-022-03758-z

[8] Symeonidis, P., Malakoudis, D. (2019). Multi-modal matrix factorization with side information for recommending massive open online courses. Expert Systems with Applications, 118: 261-271. https://doi.org/10.1016/j.eswa.2018.09.053

[9] Boratto, L., Fenu, G., Marras, M. (2019). The effect of algorithmic bias on recommender systems for massive open online courses. In European Conference on Information Retrieval, pp. 457-472. https://doi.org/10.1007/978-3-030-15712-8_30

[10] Pang, Y., Liao, C., Tan, W., Wu, Y., Zhou, C. (2018). Recommendation for MOOC with learner neighbors and learning series. In International Conference on Web Information Systems Engineering, pp. 379-394. https://doi.org/10.1007/978-3-030-02925-8_27

[11] Zhang, H., Huang, T., Lv, Z., Liu, S., Yang, H. (2019). MOOCRC: A highly accurate resource recommendation model for use in MOOC environments. Mobile Networks and Applications, 24(1): 34-46. https://doi.org/10.1007/s11036-018-1131-y

[12] Sabnis, V., Tejaswini, P.D., Sharvani, G.S. (2018). Course recommendations in moocs: Techniques and evaluation. In 2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS), pp. 59-66. https://doi.org/10.1109/CSITSS.2018.8768755

[13] Prabhakar, S., Spanakis, G., Zaiane, O. (2017). Reciprocal recommender system for learners in massive open online courses (MOOCs). In International Conference on Web-Based Learning, pp. 157-167. https://doi.org/10.48550/arXiv.1707.00331

[14] Furukawa, M., Yamaji, K. (2017). Adaptive recommendation of teaching materials based on free descriptions in MOOC course. In 2017 6th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), pp. 1011-1012. https://doi.org/1011-1012. 10.1109/IIAI-AAI.2017.176

[15] Su, Y.S., Ding, T.J., Lue, J.H., Lai, C.F., Su, C.N. (2017). Applying big data analysis technique to students' learning behavior and learning resource recommendation in a MOOCs course. In 2017 International Conference on Applied System Innovation (ICASI), pp. 1229-1230. https://doi.org/10.1109/ICASI.2017.7988114

[16] Zhang, H., Yang, H., Huang, T., Zhan, G. (2017). DBNCF: Personalized courses recommendation system based on DBN in MOOC environment. In 2017 International Symposium on Educational Technology (ISET), pp. 106-108. https://doi.org/106-108.10.1109/ISET.2017.33

[17] Zhang, H., Huang, T., Lv, Z., Liu, S., Zhou, Z. (2018).

MCRS: A course recommendation system for MOOC. In Multimedia Tools and Applications, pp. 7051-7069. https://doi.org/10.1007/s11042-017-4620-2
[18] Li, Y., Li, H. (2017). MOOC-FRS: A new fusion recommender system for MOOCs. In 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), pp. 1481-1488. https://doi.org/10.1109/IAEAC.2017.8054260
[19] Bouzayane S., Saad I., Kassel G., Gargouri F. (2017). Recommandation basée sur l'aide multicritère à la décision pour personnaliser l'échange d'information. Ingénierie des Systèmes d'Information, 22(6): 71-91. https://doi.org/10.3166/isi.22.6.71-91
[20] Ouertani, H.C., Alawadh, M.M. (2017). MOOCs recommender system: A recommender system for the massive open online courses. In Innovations in Smart Learning, pp. 139-143. https://doi.org/10.1007/978-981-10-2419-1_20
[21] Garg, V., Tiwari, R. (2016). Hybrid massive open online course (MOOC) recommendation system using machine learning. In International Conference on Recent Trends in Engineering, Science & Technology-(ICRTEST 2016), pp. 1-5. https://doi.org/10.1049/cp.2016.1479
[22] Hou, Y., Zhou, P., Wang, T., Yu, L., Hu, Y., Wu, D. (2016). Context-aware online learning for course recommendation of MOOC big data. arXiv preprint arXiv:1610.03147. https://doi.org/10.48550/arXiv.1610.03147
[23] Ding, Y.H., Wang, D.Q., Zhang, Y.X., Li, L. (2015). A group recommender system for online course study. 2015 7th International Conference on Information Technology in Medicine and Education (ITME), pp. 318-320. https://doi.org/10.1109/ITME.2015.99
[24] Bousbahi, F., Chorfi, H. (2015). MOOC-Rec: A case based recommender system for MOOCs. Procedia-Social and Behavioral Sciences, 195: 1813-1822. https://doi.org/10.1016/j.sbspro.2015.06.395
[25] Fu, D., Liu, Q., Zhang, S., Wang, J. (2015). The undergraduate-oriented framework of MOOCs recommender system. In 2015 International Symposium on Educational Technology (ISET), pp. 115-119. https://doi.org/10.1109/ISET.2015.31
[26] Onah, D.F.O., Sinclair, J.E. (2015). Collaborative filtering recommendation system: A framework in massive open online courses. INTED2015 Proceedings, pp. 1249-1257. https://doi.org/10.13140/RG.2.1.5023.4409
[27] Aher, S.B., Lobo, L.M.R.J. (2013). Combination of machine learning algorithms for recommendation of courses in E-Learning System based on historical data. Knowledge-Based Systems, 51: 1-14. https://doi.org/10.1016/j.knosys.2013.04.015
[28] Potts, B.A., Khosravi, H., Reidsema, C., Bakharia, A., Belonogoff, M., Fleming, M. (2018). Reciprocal peer recommendation for learning purposes. In Proceedings of the 8th international Conference on Learning Analytics and knowledge, pp. 226-235. https://doi.org/10.1145/3170358.3170400
[29] Bouchet, F., Labarthe, H., Bachelet, R., Yacef, K. (2017). Who wants to chat on a MOOC? Lessons from a peer recommender system. In European Conference on Massive Open Online Courses, pp. 150-159. https://doi.org/10.1007/978-3-319-59044-8_17
[30] Sunar, A.S., Abdullah, N.A., White, S., Davis, H.C. (2015). Analysing and predicting recurrent interactions among learners during online discussions in a MOOC. Proceedings of the 11th International Conference on Knowledge Management ICKM.
[31] Dai, K., Vilas, A.F., Redondo, R.P.D. (2017). A new MOOCs' recommendation framework based on LinkedIn data. Innovations in Smart Learning, pp. 19-22. https://doi.org/10.1007/978-981-10-2419-1_3
[32] Belarbi, N., Chafiq, N., Talbi, M., Namir, A., Benlahmar, H. (2018). A recommender system for videos suggestion in a SPOC: A proposed personalized learning method. In International Conference on Big Data and Smart Digital Environment, pp. 92-101. https://doi.org/10.1007/978-3-030-12048-1_12
[33] Cooper, M., Zhao, J., Bhatt, C., Shamma, D.A. (2018). MOOCex: Exploring educational video via recommendation. In Proceedings of the 2018 ACM on International Conference on Multimedia Retrieval, pp. 521-524. https://doi.org/10.1145/3206025.3206087
[34] Cooper, M., Zhao, J., Bhatt, C., Shamma, D.A. (2018). Using recommendation to explore educational video. In K. Aizawa, M. Lew, S. Satoh (Chairs), ACM International Conference on Multimedia Retrieval (ICMR). https://doi.org/10.475/123_4
[35] Zhao, J., Bhatt, C., Cooper, M., Shamma, D.A. (2018). Flexible learning with semantic visual exploration and sequence-based recommendation of MOOC videos. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, pp. 1-13. https://doi.org/10.1145/3173574.3173903
[36] Bhatt, C., Cooper, M., Zhao, J. (2018). SeqSense: Video recommendation using topic sequence mining. In International Conference on Multimedia Modeling, pp. 252-263. https://doi.org/10.1007/978-3-319-73600-6_22
[37] Agrawal, A., Venkatraman, J., Leonard, S., Paepcke, A. (2015). YouEDU: addressing confusion in MOOC discussion forums by recommending instructional video clips. Proceedings of the 8th International Conference on Educational Data Mining, pp. 297-304.
[38] Harrathi, M., Touzani, N., Braham, R. (2018). Toward a personalized recommender system for learning activities in the context of MOOCs. In International Conference on Intelligent Interactive Multimedia Systems and Services, pp. 575-583. https://doi.org/10.1007/978-3-319-59480-4_57
[39] Hajri, H., Bourda, Y., Popineau, F. (2017). MORS: A system for recommending OERs in a MOOC. In 2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT), pp. 50-52. https://doi.org/10.1109/ICALT.2017.89
[40] Chen, G., Davis, D., Krause, M., Aivaloglou, E., Hauff, C., Houben, G.J. (2016). From learners to earners: Enabling MOOC learners to apply their skills and earn money in an online market place. IEEE Transactions on Learning Technologies, 11(2): 264-274. https://doi.org/10.1109/TLT.2016.2614302
[41] Chen, G., Davis, D., Krause, M., Hauff, C., Houben, G.J. (2017). Buying time: Enabling learners to become earners with a real-world paid task recommender system. In Proceedings of the Seventh International Learning Analytics & Knowledge Conference, pp. 578-579. https://doi.org/10.1145/3027385.3029469
[42] Chen, G., Davis, D., Krause, M., Aivaloglou, E., Hauff, C., Houben, G.J., ICSI, U. (2016). Can learners be

earners? Investigating a design to enable MOOC learners to apply their skills and earn money in an online market place. IEEE Transactions on Learning Technologies, pp. 1-12. https://doi.org/10.1109/TLT.2016.2614302
[43] Jain, H. (2018). Applying data mining techniques for generating MOOCs recommendations on the basis of learners online activity. In 2018 IEEE 6th International Conference on MOOCs, Innovation and Technology in Education (MITE), pp. 6-13. https://doi.org/10.1109/MITE.2018.8747056
[44] Holotescu, C., Holotescu, V. (2016). MOOCBuddy: A chatbot for personalized learning with MOOCs. Proceedings of the 13th International Conference on Human-Computer Interaction RoCHI'2016, pp. 91-94.
[45] Yang, D., Piergallini, M., Howley, I., Rose, C. (2014). Forum thread recommendation for massive open online courses. Proceedings of the 7th International Conference on Educational Data Mining.
[46] Yang, D., Shang, J., Rosé, C.P. (2014). Constrained question recommendation in MOOCs via submodularity. In Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management, pp. 1987-1990. https://doi.org/10.1145/2661829.2662089
[47] Piao, G., Breslin, J.G. (2016). Analyzing MOOC entries of professionals on LinkedIn for user modeling and personalized MOOC recommendations. In Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization, pp. 291-292. https://doi.org/10.1145/2930238.2930264
[48] Agrebi, M., Sendi, M., Abed, M. (2019). Deep reinforcement learning for personalized recommendation of distance learning. In World Conference on Information Systems and Technologies, pp. 597-606. https://doi.org/10.1007/978-3-030-16184-2_57
[49] Jing, X., Tang, J. (2017). Guess you like: course recommendation in MOOCs. In Proceedings of the International Conference on Web Intelligence, pp. 783-789. https://doi.org/10.1145/3106426.3106478
[50] Zhang, H., Huang, T., Lv, Z., Liu, S., Yang, H. (2019). MOOCRC: A highly accurate resource recommendation model for use in MOOC environments. Mobile Networks and Applications, 24(1): 34-46. https://doi.org/10.1007/s11036-018-1131-y
[51] Xiao, J., Wang, M., Jiang, B., Li, J. (2018). A personalized recommendation system with combinational algorithm for online learning. Journal of Ambient Intelligence and Humanized Computing, 9(3): 667-677. https://doi.org/10.1007/s12652-017-0466-8
[52] Fauzan, F., Nurjanah, D., Rismala, R. (2020). Apriori association rule for course recommender system. Indonesia Journal on Computing (Indo-JC), 5(2): 1-16. https://doi.org/10.21108/indojc.2020.5.2.434