A Systematic Mapping Review on MOOC Recommender Systems

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This work was supported in part by the European Research Consortium for Informatics and Mathematics (ERCIM) “Alain Benoussan” Fellowship Programme under Contract 2019–40, and in part by the Color and Visual Computing Laboratory, Department of Computer Science, NTNU, Gjøvik.

ABSTRACT Online learning environments (OLE) including learning management systems (LMS) and massive open online courses (MOOCs) are gaining popularity as the best modern alternate solutions available for education in the current era. The luxury to learn irrespective of geographical and temporal restrictions makes it an attractive resource. At the start of 2020, the global pandemic enforced social distance practice worldwide, changing the work environment dynamics, leaving options like online trading, work from home, and online education. Online learning environments gained particular attention in the educational sector, where users could access the online learning resources to fulfil their academic requirements during the lockdown. From massively available content such as MOOC, learners are overwhelmed with the available choices. In this scenario, recommender systems (RS) come to the rescue to help the learner make appropriate choices for completing the enrolled course. There is tremendous scope and a multitude of opportunities available for researchers to focus on this domain. An exhaustive analysis is required to spotlight the opportunities in this realm. Various studies have been performed to provide such solutions in multiple areas of the MOOC recommendation systems (MOOCRS) such as course recommendation, learner peer recommendation, resource recommendations, to name a few. This is a compendious study into the research conducted in this area, identifying 670 articles out of 116 selected for analysis published from 2013 to 2021. It also highlights multiple areas in MOOC, where the recommendation is required, as well as technologies used by other researchers to provide solutions over time.

INDEX TERMS Deep learning, learning analytics, machine learning, MOOC, personalized learning, recommender systems.

I. INTRODUCTION

The recent coronavirus (SARS-CoV2 or CoVid-19) outbreak and its rapid spread across the globe has emphasized social distancing and has changed the dynamics of work in every sphere of life, including education [1]. In this situation, online education is one of the preferred options for students and organizations [2], where anyone can learn any general or specific topic of interest using online sources [3], regardless of their geographical or temporal constraints. These modern pedagogy practices promote open educational resources (OER) publication to ensure educational transparency [4]. Some of the world’s top universities are offering high quality and superior courses to the learners across the globe by adapting OpenCourseWare (OCW) [5]. Among such options, Massive open online courses (MOOC) are one of the foremost choices for online education and have attained acceptance in last decade. MOOCs have grown exponentially and have surpassed social networks [6], and this is viewed as the foremost technological innovation in the last 200 years [7]. The inception of the term MOOC was initially instigated in 2008 by Dave Cormier to outline George Siemens and Stephen Downes online course ‘CCK08’ [8]. MOOCs are further classified into two categories, cMOOC (Connectivist-Massive
Online Course) and xMOOC (Extended-Massive Open Online Course) [9]. cMOOC involves groups of people learning together and often uses blogs, learning communities, and social media platforms. Examples of cMOOC include MOOC course “CCK08-Connectivism and Connective knowledge” offered by the University of Manitoba in 2008 [10], [11], Alec Couros’s course in education “Social media and open education” offered by University of Regina in 2007-2008 and “Personal Learning Environments, Networks and Knowledge” offered by the Athabasca University [9], [12], [13]. In 2011, Sebastian Thrun launched a course on Artificial Intelligence at Stanford University, which was different from the cMOOC with predefined learning paths and goals for the learner. These MOOCs that are teacher centric, and provide content to large audiences based on transfer of knowledge from teacher to learner are known as xMOOC [14]. Most of the MOOCs come under this category as they do not follow principles of connectivism solely [15]. In 2012, many leading universities created more than ten thousand study courses in MOOCs such as edX, Udacity and Coursera, and enrolled millions of students [16], [17]. More than 900 universities offered 11,400 courses on MOOC until the end of 2018 [18]. Despite the high enrollment in MOOC, the student dropout rate is stated to be approximately 90% [19], [20]. A study compiled by EDX shows that 17% of the enrolled learners consulted the course, and only 8% completed their certification, meaning that the majority of the enrolled students do not complete their course [21]. Therefore, the issue of attrition in MOOC and the factors contributing to it, have been the focus of many studies [22]–[24]. One such factor may be information overload. The growing number MOOC platforms and courses they offer [15] consequently overwhelm the learner with information overload [25]. One wrong choice can make it harder for the students to complete a course because of massive available choices, resulting in a dropout [26]–[28].

A. BACKGROUND
As the recommender systems (RS) have shown promising results in business and e-commerce by helping the consumers in recommending the appropriate products, they can provide a personalized/adaptive learning environment and suggesting appropriate MOOC resources to the learner [11]. RS in MOOC delivers personalized recommendations for learning resources, based on learner interest [29]–[32]. Studies are conducted to overcome this challenge [28] for the development of recommender systems that are adaptive to the learner for personalized learning [28], [33].

RSs are software tools and techniques that provide recommendations to the user from numerous available items [33] by discovering different pattern in the datasets. RSs were initially used as ‘digital’ bookshelves in research [34]

1https://sites.google.com/site/themoocguide/3-cck08—the-distributed-course
2http://eci831.ca/about/
3https://tekri.athabascau.ca/content/personal-learning-environments-networks-and-knowledge

but gained popularity for commercial use after Goldberg et al. [35] developed Tapestry [Xiao, 2018 #12; Gupta, 2019 #10], which recommended documents extracted from the newsgroups to its users. Recommender systems can be broadly divided into two basic models, collaborative filtering RS and content based RS [36], [37]. Collaborative filtering RS provides recommendations based on the assumption that similar kinds of users have similar tastes, and similar choices can be expected from them in future. They are closely related to missing value analysis. The content-based RS consider profile of both users and items. It uses descriptive attributes ‘contents’ of items to make recommendations. Further, there are knowledge-based RS models and Hybrid systems. Knowledge based models are based on users’ requirements, specified explicitly using external knowledge bases and constraints and do not rely on historical rating or user profile. They can be further divided into constraint-based recommender systems [38], [39] where users typically specify constraints and requirements, and case based recommender systems [40]–[43] where cases are specified by the user as anchor points or targets and similarity metrics are defined on the item attributes to retrieve similar items to these cases. Hybrid systems combine strengths of various RS techniques and it can perform more robustly in variety of settings [44]. These systems are closely related to the field of ensemble analysis where the power of multiple type of machine learning algorithms is combined to create a more robust model. Hybrid RS not only combine the power of multiple data sources, but they are also able to improve the effectiveness of a particular class of recommender systems by combining multiple models of the same type. In this study, we have further classified RS used in MOOC based on the techniques used.

B. RELEVANT SURVEYS
A number of surveys are conducted in the domain of eLearning RS [45]–[48], RS in general [49]–[51], review of the factors that affecting MOOC quality [52], but to the best of our knowledge only 3 survey focuses on MOOCSRS [11], [15], [53]. Sunar et al. [11] classified 40 selected studies between 2011 and 2014 based on needs (why RS are required), proposals (the studies that involved funded projects for the personalization of online education) and implementations (studies with approaches for implementing personalization of MOOC). Khalid et al. [15] covered 79 studies between 2012-2019 and classified them in different categories based on the solution they provide, categorized authors into groups, discussed datasets used, and classified them according to the countries. Finally Kusumas- tuti [53] reviewed 34 studies between 2016-2020 with adaptive learning models and classified them according to the learner models and algorithms used in the studies. Table 1 presents some of the latest surveys along with their features and limitations.

The limitations and findings shown in Table 1 provide a base for conducting a comprehensive study on massive open
| Reference Survey                                                                 | Features                                                                                                                                                                                                 | Remarks                                                                                                                                                                                                 |
|---------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| The state of the art in the methodologies of course Recommender Systems- A review of recent research (2021) [45] | Review of the studies performed between 2016 to June 2020. Different recommendation approaches are used in detail. Detailed review of the course recommender systems in general, 155 studies selected. Categorized studies into different models depending on the techniques used to achieve course recommenders. | • Not specific to MOOC recommenders, but course recommenders in any platform. • No datasets explored • No funding agencies mentioned                                                                 |
| Models of Adaptive learning systems in MOOC: A Systematic Literature Review (2021) [53] | Systematic literature review of MOOC based adaptive learning models reviewed from 2016-2020. 34 studies identified. Categorization of selected studies into different learner models (content model, learner model and instructional design model). Explored the algorithms used in the selected studies. | • Only adaptive learning models were discussed with time period 2016-2020 • No datasets explored • No funding agencies mentioned                                                                 |
| A Comprehensive review of Course recommender systems in e-learning (2021) [46] | Course recommender systems in general discussed. Studies categorized based on different recommender techniques used. Role of learning modeling in recommendation discussed. Parameters and techniques of existing work highlighted. Taxonomy of factors in Course recommendation systems highlighted. | • Not specific to MOOC • Number of studies selected not mentioned • No search criteria or protocol defined • No time period defined • No repositories defined • No datasets explored • No funding agencies mentioned |
| Recommender Systems for MOOCs: A Systematic Literature Survey(2020) [15]          | Systematic literature review of MOOC from 2012 to 2019. 79 Studies discussed. Discussed papers where MOOC RS is proposed, discussed or implemented. Discussed recommender types, categorized authors into groups. Classified literature based on research concerns (recommendations), country and yearly distributions. | • No technologies were discussed • No datasets were explored • No funding agencies mentioned                                                                                                               |
| Recommender System in eLearning: A Survey (2020) [47]                           | Targets real world application development for RS. It examines the RS systems base types and in different domains like news, e-business etc. Introduced explicit and implicit feedback challenges.                                | • Short Paper with 20 references • Focused on classic recommender systems • Discussed general e-learning and does not focus on MOOCRS                                                                                 |
| Deep learning based recommender systems (2019) [49]                             | Comprehensive overview of the recent research in the area of deep-learning based recommender systems by highlighting techniques and limitations. Differentiated RS with neural building blocks from RS with deep hybrid models. Provide list of apps with deep neural network-based RS models. | • Discussed RS in general domain and not Specific to MOOCRS.                                                                                                                                              |
| A systematic review: Machine learning based recommendation systems for e-learning (2019) [48] | Reviews recommender systems in eLearning domain that use the Machine learning approach. Discussed data and evaluation metrics used in RS. Classified papers based on Collaborative Filtering, Content based and Hybrid Approach. Discussed cold start problem and quality of RS. Explained attributes of and instances used in e-learning RS | • Time period is very short (2016-2018) • 35 papers are discussed • Domain is eLearning, but does not discuss MOOCRS                                                                                   |
| A survey of recommender systems based on deep learning (2018) [50]              | Explored deep learning technology and type of models. Discussed and compared social network and context aware recommender systems based on deep learning. Focused on Attention mechanism and Deep composite models along with Cross Domain recommender systems based on DL. | • Only discusses deep learning-based RS. • Domain is general and no MOOCs discussed.                                                                                                                    |
| The use of machine learning algorithms in recommender systems: A Systematic Review (2018) [51] | Systematic review of 26 studies that focused on recommender systems that use ML algorithms. Highlights some of the RS systems that use mathematical or statistical techniques. | • The domain is not MOOCRS • Only 26 papers are included. Only RS based on Machine learning are discussed.                                                                                             |
| Personalization of MOOCs- The state of the art (2015) [11]                    | Studies between 2011 and 2014 were analyzed. Peer review articles along with the grey literature was selected. Need for personalization of MOOC was discussed. Papers were categorized into Proposals and implementations. | • Time period 2011-2014 • 40 studies Selected • No datasets discussed.                                                                                                                                    |
| Quality of MOOCs: A review of literature on effectiveness and quality aspects (2015) [52] | Studies between 2012-2015 were analyzed. Factors that affect effectiveness of MOOC, Dimensions/categories/elements that make quality MOOC. | • Time period 2012-2015 • 26 Papers Selected • The Domain is MOOC • No MOOCRS discussed                                                                                                            |
online course recommender systems (MOOCRS). Therefore, our survey focuses on studies conducted in time frame from 2013-2021 and reviewed 116 studies. This is the first of its type to present the domain in a very comprehensive manner by classifying the studies with respect to type of recommendations, technologies or techniques used, type of publication, year wise distribution of studies, countries, datasets and funding agencies.

This study focuses on identifying potential research avenues in the domain with respect to technologies, techniques and datasets used for developing MOOCRS. This identification will help researchers understand the evolution of MOOCRS. The literature studied in this survey shows no clear boundaries and areas, and most recommendations are vague, with no precise classification of areas defined inside the MOOC domain. Summary of the contributions for this study are as follows:

1. This study aims to fill in the gap in the literature by providing a comprehensive systematic mapping survey in the area of MOOCRS to help future researchers to get a better insight into this publication domain.
2. The survey explores the trends, technologies and their evaluation metrics in the MOOCRS literature. It also classifies MOOCRS based on their functions and recommendations.
3. The survey explores and organizes the current literature from 2013-2021 with respect to multiple variables including publications, publishers, dataset and funding agencies, in order to guide the future researchers in this domain.
4. The challenges of MOOCRS methods and identified along with the conclusions from the surveyed literature.

The structure of the paper is as follows: Section I presents the scope, outline, and coverage of the survey; Section II includes the research methodology used to conduct the survey; Section III discusses ‘Results and discussions’ and provides answers to the research questions; and Section IV summarizes the conclusions extracted from the study and discusses future directions.

II. RESEARCH METHOD
This study aims to investigate the contemporary state-of-the-art on MOOCRS to identify most common and successful techniques, methods. This study uses a type of systematic review technique called mapping study or scoping study [54]. It provides a comprehensive survey of the research domain and identifies the quantification, research types, techniques and datasets in the literature. This systematic review follows proposed guidelines by Kitchenham et al. [32].

The procedure comprises of following major phases:
A. Specifying research questions.
B. Search strategy.
C. Identification of primary studies
D. Data extraction
E. Threat to validity

A. RESEARCH QUESTIONS
The prime question that leads this review is what areas, technologies, datasets, evaluation metrics are used when developing MOOCRS. To pipeline this systematic mapping review this key question was split into seven research questions, which are shown in Table 2. This would clearly portray the roadmap of the study and would help the reader in grasping the intended insights.

| RQ# | Research Questions                                                    | Motivation                                      |
|-----|------------------------------------------------------------------------|-------------------------------------------------|
| RQ1 | How many studies supported their claim with experiments and which datasets were used in the studies? | Underline the studies that were supported by ‘experiments and results’ and what datasets were used in experiments. |
| RQ2 | What are the type of MOOCRS found in the literature?                   | Identify which elements of MOOC the RS recommends |
| RQ3 | What technologies and techniques are used to implement MOOCRS in the literature? | To identify technologies used to develop MOOCRS |
| RQ4 | What were the evaluation metrics used to evaluate the experiments in the literature? | Check what are the different evaluation metrics used in the literature |
| RQ5 | Which countries are involved in MOOCRS research?                       | Highlight countries that are actively working in the realm of MOOCRS |
| RQ6 | What are the popular trends based on technologies used and type of recommendation in MOOCRS? | Accentuate the technologies and MOOCRS types |
| RQ7 | How many studies in the literature were funded and by which funding agency? | Highlight funding agencies that have funded such studies and could be seen as potential funding source for future studies |

B. SEARCH STRATEGY
The strategy adopted in this study is to identify primary studies on MOOCRS in literature includes identification of search strings, time period, selection of digital repositories and identification of primary studies. These are discussed in the following subsection.

1) SEARCH STRINGS
We defined three sets of search strings to perform our search, which are MOOC Recommender Systems, MOOC Recommendation Systems, MOOC Recommendations.

2) TIME PERIOD
This study focuses on the time-period starting from 2013 to 2021, inclusive. The MOOC kicked off in 2008, the concept started emerging in 2012, but in 2013 the first MOOCRS.

3) SELECTION OF DIGITAL REPOSITORIES
We used Mendeley Desktop Application for primary search and then re-checked well-known repositories if we have missed any paper. Table 3 shows Mendeley results from various search strings.
Repositories used for re-searching the papers were IEEE-EXplore, ACM Digital Library, Science Direct and Google Scholar. The first three peer-reviewed repositories are relevant to Computer Science and provide pertinent results. Simultaneously, Google Scholar was used to fine-grain our search and look for any literature that might be missed.

### C. IDENTIFICATION OF PRIMARY STUDIES

The selected search strings were applied in digital repositories on the keywords, titles and abstracts to extract relevant papers. The steps devised to search for the primary studies are shown in Figure 1.

#### FIGURE 1. Identification process of primary studies.

**Search:** We achieved 196 studies initially in the Mendeley desktop application and 781 when searched in the well-known repositories, as shown in Table 4.

#### TABLE 4. Studies Found in different digital repositories.

| Repository          | Studies Found Initially | Selected Studies |
|---------------------|-------------------------|------------------|
| IEEE-EXplore        | 117                     | 46               |
| Science Direct      | 126                     | 20               |
| ACM Digital Library | 228                     | 23               |
| Google Scholar      | 310                     | 27               |
| **Total**           | **781**                 | **116**          |

**Screening:** In this step, we first discarded duplicate papers, and the papers that had a non-English language. Further, we discarded papers that had the word ‘recommendation’ in their titles, abstract or in the keywords, but were not relevant to our domain. Moreover, studies with insufficient details about the research were excluded. Following the criteria defined in Table 5 for exclusion and inclusion, the number of primary studies extracted reduced to 611 at the end of the screening process.

#### TABLE 5. Inclusion and exclusion criteria.

| Inclusion Criteria | Exclusion Criteria |
|--------------------|--------------------|
| 1. Search String must appear in title, abstract or keywords of the study. | 1. Abstracts, keynote and studies having abstract in languages other than English. |
| 2. Studies written in English language. | 2. Same studies indexed in more than one digital repository to avoid duplication. |
| 3. Studies published in Journals, Conferences and Book chapter during 2013-2021. | 3. Studies in which recommendation meant something else. |
| 4. Studies that had insufficient information about their research, dataset or what they recommended. | 4. Studies that had insufficient information about their research, dataset or what they recommended. |
| 5. Studies where full text was unavailable. | 5. Studies where full text was unavailable. |

**Included:** Finally, 116 studies were selected for thorough investigation and analysis by excluding the studies with primary focus on concepts other than MOOCRS. For example, excluded were studies that recommended policies and practices for MOOC, design, and development of e-learning systems, or learning analytics that mentioned MOOCRS in abstract but were not relevant to the domain. Some of the studies were extended versions of the same article, and so only the latest version was included in full-text analysis after careful study of each version.

Amongst the 116 selected papers, 91 were conference papers, 24 belonged to Journals, and 1 was a book chapter. Figure 2 shows the distribution of studies. Figure 3 and Figure 4 show the number of selected papers published in journals and conferences between 2013-2021. Table 6 shows the year wise summary of the papers, their types, and publishers.

#### FIGURE 2. Distribution of selected literature (2013-2021).

#### FIGURE 3. Studies published in Journals between 2013-2021.
During this search, we have identified journals that support this domain, and these are shown in Table 7. This information can help future researchers when publishing their research in this domain. Figure 3 shows that 2017 to 2021 (May 2021 at the time of this writing) increasing trend of MOOCRS published in Journals, which clearly depicts the importance of the domain.

### Table 7. List of Journals and number of studies found.

| Name                                      | Publisher               | Count |
|-------------------------------------------|-------------------------|-------|
| Knowledge-Based Systems                   | Science Direct          | 1     |
| Procedia – Social and Behavioral Sciences | Elsevier                | 1     |
| Revista Iberica de Sistemas e Tecnologias de Informacao | RISTI                | 1     |
| Computer Applications in Engineering Education | John Wiley & Sons   | 2     |
| International Journal of Electrical and Computer Engineering (IJEECE) | IEEE                | 1     |
| Wireless Personal Communications          | Springer                | 1     |
| International Journal of Crowd Science   | Emerald Publishing     | 1     |
| Multimedia Tools and Applications         | Springer                | 1     |
| World Wide Web Internet and Web Information Systems | Springer            | 1     |
| Mobile Network Applications               | Springer                | 1     |
| Computational Social Networks             | Springer                | 1     |
| IEEE Access                               | IEEE                    | 2     |
| Soft Computing                            | Springer                | 1     |
| International Journal of Recent Contributions from Engineering, Science & IT (IJES) | IOPscience            | 1     |
| Journal of Physics: Conference Series     | Hindawi                 | 1     |
| Wireless Communication & Mobile Computing | Indo-JC                 | 1     |
| Indonesia Journal of Computing (Indo-JC)  | JET                     | 1     |
| International Journal of Emerging Technologies in Learning (IJET) | PLOS ONE              | 1     |
| PLOS ONE                                  | PLOS ONE                | 1     |
| Complexity                                 | Hindawi                 | 1     |
| Australian Journal of Educational Technology (AJET) | AHMET                | 1     |

### D. DATA EXTRACTION

In this step, we extracted data from 116 studies for our investigation. A tabulated Microsoft Excel spreadsheet was used to log the data. A unique identification key (Study_ID) consisting of the author’s name and publication year was assigned to each study. The sheet was used to code the following extracted elements: ‘Study_ID’ to identify each study uniquely, ‘Publication type’ to show if it belongs to a journal or conference (as we have only 1 book chapter [100], we have categorized it under conferences). ‘Type of RS’ represents what type of MOOC RS is focused in the study, ‘Techniques used for RS’ highlights the technique used in the study to achieve the goals. ‘Datasets’, ‘Evaluation Matric’ in cases experiments were performed and evaluated followed by the ‘Country’ representing country where research was performed, ‘Funding status’ shows the funding status, and ‘Funding Agency’ represents agency that funded the study. Table 8 provides description of each element.

### E. THREATS TO VALIDITY

The threats to the validity are not based on human intervention and are purely internal. They are as follows:
Search String: A slight probability exists such that we might have missed a study on MOOCRS in the domain of Computer Science, even after searching multiple domains to double-check, following the initial query on Mendeley. However, we consider the possibility of missing a study to be negligible and a minor threat.

Temporal audience and search coverage: We have included studies between January 2013 and May 2021, and studies after this time are not included.

Selection of publication resources: Although we initially queried our search in Mendeley, we used other digital repositories too. We tried including almost all of the available studies published in any journal, conference, or book to give a comprehensive overview of the research in this domain.

Data Analysis of studies: We followed Kitchenham et al. [31], which states that two analysts or one analyst with a peer to review should carry out data extraction and verify the percentage. In this study, one author, followed by the peer reviewers performed data extraction.

III. FINDINGS AND DISCUSSIONS
In this section, we will try to answer the research questions posted in Table 2.

A. RQ1. HOW MANY STUDIES SUPPORTED THEIR CLAIM WITH EXPERIMENTS AND WHICH DATASETS WERE USED IN THE STUDIES?
The selected literature included total of 116 papers, out of which 70 articles had their study validated with experiments on specific datasets. Out of 70, 60 mentioned datasets explicitly while remaining 10 did not mentioned the datasets nor their source. Forty-six papers mentioned the framework, concept, or ideas but proposed experiments and implementation in future work. Only one study, i.e., Li and Mitros [63], shared code and documentation under open license on GitHub.

Studies that showed no experiments were included in the literature because they portrayed the researcher’s idea for the solution to challenges in MOOCRS. The papers that included experiments used either publicly available datasets or used private datasets belonging to from different platforms and universities. There were few papers that did not mention datasets used nor specified any link to the dataset. Seventy papers have clearly mentioned the datasets used. Sixteen of the 60 total datasets found were open datasets, while 44 were closed dataset. Amongst the open datasets, 5 require sending request to the dataset providing platform such as Coursera or edX or email to the author. Table 9 highlights the datasets used and references to studies that used those datasets.

The data in the literature shows datasets are not easily available. Due to the dynamic nature of the MOOC, platform contains combination of multimedia, social, learner profile, learner progress, geographical and temporal data, hence MOOC can provide huge amount of data. All this information related to a single platform combined is not accessible nor available, which can help build a strong recommender system, and most of the researchers have used their private LMS data or publicly available data from sources like edX, Coursera, HarvardX using relevant APIs. This is a serious constraint when comparing algorithms or benchmark techniques with other baselines techniques. The domain requires open rich datasets for MOOCRS that can be used to evaluate experiments. Another limitation is that most of the studies have focused on the domain of computer science, which restricts the study to single field in academia.

B. RQ2. WHAT ARE THE TYPES OF MOOCRS FOUND IN THE LITERATURE?
MOOCRS can classified into of different types based on their recommendations. A typical learner who wants to enroll in a MOOC course has to select one of the many available options. We have classified the MOOCRS broadly into the following nine types, based on the what they recommend. The discussion on these types includes the research conducted in these domains:

1. MOOC recommender
2. Adaptive Learning
3. Personalized learning
4. Pre-requisite recommender
5. LO recommender
6. Content Recommender
7. Course recommender
8. Resource recommender
9. Social recommender

1) MOOC recommender
This recommender is helpful to learners in picking an appropriate platform for a course. Sometimes, a course is offered by more than one MOOC platform and picking an appropriate MOOC platform that is most suitable for the learner is a challenge. To overcome this issue, Piao and Breslin [78] used ontology modeling using learners’ educational skills, technical skills and job titles from LinkedIn and showed that skill-based data for user modeling produces better results. Assami et al. [150] proposed a three layer MOOC recommender system that utilized learner modeling combined

Table 9: Types of MOOCRS

| Type of MOOCRS | Description |
|---------------|-------------|
| MOOC recommender | Helps learners to pick an appropriate platform |
| Adaptive Learning | Learners are provided with adaptive learning content |
| Personalized Learning | Learners receive personalized learning content |
| Pre-requisite recommender | Learners are provided with pre-requisite courses |
| LO recommender | Learners are provided with courses based on their Learning Objectives |
| Content Recommender | Learners are provided with recommended content based on their interests |
| Course recommender | Learners are provided with recommended courses based on their skills |
| Resource recommender | Learners are provided with recommended resources based on their needs |
| Social recommender | Learners are provided with recommended social interactions |

Table 8: Elements of the studies.

| Elements | Details |
|----------|---------|
| Study ID | Author and the publication year |
| Publication Type | Journal or Conference |
| Type of RS | What does the system recommend? |
| Techniques used for RS | Identify the employed techniques? |
| Dataset Used | What Data Sets are used? |
| Evaluation Metric | Evaluation metric used for evaluation of experiments |
| Country | Country focusing on MOOCRS research |
| Funding Status | If the research is funded or not? |
| Funding Agency | If funded, what agency funded the research? |

4https://github.com/pmitros/RecommenderXBlock
5https://www.coursera.org/
### TABLE 9. Dataset summary.

| Studies | Datasets | Access                        |
|---------|----------|-------------------------------|
| [55]    | LMS Moodle Data                   | Closed                        |
| [57]    | Data of learning objects (LO's) under the subject “CSE 101” for 135 learners | Closed                        |
| [58]    | Peruvian University’s student dataset | Closed                        |
| [59]    | Coursera Discussion forums, 1. ‘Accountable Talk: Conversation Works, 2. ‘Fantasy and Science Fiction: the human mind, our modern world’ Courses | Require Request from Coursera|
| [60, 61]| Coursera course: ‘Learn to Program: The Fundamentals’, (Python Course) with 3590 active students and 3079 threads across around eight weeks | Require Request from Coursera|
| [62]    | Coursera Real Dataset and Shandong Normal University course Dataset | Closed                        |
| [63]    | Massachusetts Institute of Technology dataset: 6.60.1x-Introduction to Computer Science and Programming Using Python” | Closed                        |
| [70, 99, 108, 113, 137] | Harvard and MIT dataset [171] [172] | https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/26147&version=1.0 |
| [73]    | National Tsing Hua University Introduction to Computer Networks* course on ShareCourse [173] | Closed                        |
| [75]    | Custom Dataset (81 Example Courses) and Text Retrieved from google custom search API | Closed                        |
| [77]    | 3765 user, 27 unique email items | Closed                        |
| [78]    | Dataset of Linkedin profiles having the keyword “Coursera” by creating Google Custom Search Engine (GCSE) https://www.google.ie.cse | Closed                        |
| [79]    | GdP MOOC, a French MOOC data       | Closed                        |
| [81]    | edX Course ‘Data Analysis take it the max’ and freelance site data from Upwork, Guru, etc. | Closed                        |
| [82, 83]| UC Berkley’s 13 MOOC dataset from course administered in late 2015 to 2016 from the edX platform | Closed                        |
| [84]    | CS50 at Stack Exchange Platform- Questions posted on educational CQA system (between May 2014 to February 2017) | https://archive.org/details/stackexchange |
| [85]    | Data Collected from University canvas [174] | Closed                        |
| [86]    | Real-world MOOC dataset from Coursetalk (http://www.coursetalk.com) | Closed                        |
| [87]    | JMOOC platform data (Japan) | Closed                        |
| [91]    | Custom Dataset (data of 180 Freshmen from the University of Northern Taiwan and Facebook was used) | Closed                        |
| [92]    | Parsed course details (5359) from Coursera, edX and Udacity | Closed                        |
| [93]    | Data from a job-hunting website (http://www.104.com.tw) | Closed                        |
| [96, 124]| starC MOOC platform of Central China Normal University (based on open edX platform) | Closed                        |
| [98]    | Learning Objectives LO’s from Introduction to information Technology Course at Mae Fah Luang University, Thailand. | Closed                        |
| [101]   | Forum data from the École polytechnique fédérale de Lausanne’s three courses offered on Coursera. | Closed                        |
| [103]   | Discussion forum data for three courses on Coursera | Closed                        |
| [104, 109, 158] | Scrapped 1600 open online courses data from iCourse Platform http://www.icourses.cn | Closed                        |
| [106]   | DBLP Dataset https://snap.stanford.edu/data/com-DBLP.html | Closed                        |
| [110]   | StackSample: 10% of Stack Overflow Q&A [175] https://www.kaggle.com/stackoverflow/stacksample | Closed                        |
| [111]   | Educational Video Data from YouTube and TED website (3,150 videos) | Close                          |
| [112]   | Coursera, edX, and Udacity, 4186 videos (126 GB) | Close                          |
| [113]   | IBM Almaden Quest research group Dataset | http://fimi.uantwerpen.be/data/ |
| [113]   | SPMF: A Java Open-Source Data Mining Library (philippe-fournier-viger.com) https://www.philippe-fournier-viger.com/spmf/index.php?link=datasets.php | Closed                        |
| [114, 115, 117, 118, 123] | Dataset used was obtained by recorded by the mic-video platform ECNU (East China Normal University) | Closed                        |
| [121]   | Data of about 1535 learners from a French MOOC Course ‘Design Thinking’ proposed by a Business School in France. | Closed                        |
| [122]   | Coursera course Data Structures and Algorithms from Peking University | Closed                        |
| [126, 149] | Chinese University MOOC platform data | Closed                        |
| [128]   | Movielens dataset | https://grouplens.org/datasets/movielens/ |
| [129]   | eLearning platform known as Campus Virtual at Universidad de Córdoba. | Closed                        |
| [130]   | Data Collected from the “Design a Database with UML” course from the platform OpenClassrooms using OpenEdX based MOOC. | Closed                        |
| [146]   | LIRIS-ACCEDE movie databases | https://liris-accede.ccs-d Lyon.fr/ |
| [146]   | FilmStim movie dataset | https://sites.uclouvain.be/ipsp/FilmStim/ |
with content modeling to achieve the goal. Similarly, Sebbaq et al. [160] proposed a framework for the teachers and course designers based on semantic web, ontologies, their mappings and linked data. Researchers have used topic modeling to discover the abstract topics from the documents, and Latent Dirichlet Allocation (LDA) is one of the types of statistical topic modeling techniques that is used for topic modeling. Likewise, Zarra et al. [110] used LDA Topic modeling to classify users into groups according to similar needs by extracting topics from discussion forums. Furthermore, Chao et al. [128] used a hybrid approach using matrix decomposition techniques like singular value decomposition (SVD) and restricted Boltzmann (RBM) with collaborative filtering to recommend an appropriate MOOC platform to the learner. With the growing number of MOOC there is still lot of work required in this domain as very few studies focused on recommending learner in choosing appropriate MOOC platform.

2) ADAPTIVE LEARNING
This MOOCRS is based on an adaptive learning technique that is an educational method used for interactive teaching and training devices. It provides individuals with learning programs based on relevant data, and optimizes training data to take their training to the next level [179]. A framework was proposed by Alzaghoul and Tovar [71] that used learner profile and learner experiences to provide pre-requisite recommendations along with adaptive learning facility to the learner. Similarly, González-Castro et al. [169] proposed an adaptive learning module for a conversational agent (JavaPAL) to that support learners in the successful completion of the course. This domain is catching the interest of the researchers now and has a lot of research potential to help learners according to their specific requirements.

3) PERSONALIZED LEARNING
This MOOCRS provides a highly customized focused learning path for each student [180] instead of a traditional classroom with many learners, where it is not possible for the instructor to pay them individual attention. To accomplish this, researchers have worked in multiple dimensions. Wang et al. [102] used classical collaborative filtering approach with multivariate weight algorithm MAWA using attribute weight and attribute value weight to calculate recommendation values. Likewise, Xiaoyan and Jie [126] employed bipartite graph processing and context information to improve the recommended quality of the existing collaborative filtering algorithm. Similarly, Assami et al. [133] exploited semantic/ontology-based approaches by utilizing the semantic structure of online courses and extended their work by introducing profile construction [107], social media mining [140], and proposed trace-based approach to achieve personalized learning recommendation [133]. Likewise, Slimani et al. [161] employed semantic filtering via

| TABLE 9. (Continued.) Dataset summary. |
|----------------------------------------|
| [132] Discussion forum datasets from Coursera’s: Machine Learning (ml), Algorithms, Part I(algo), and English Composition I (comp) courses (2012) | Require Request from Coursera |
| [139] STANFORD MOOCPOSTS DATASET [176] at https://datasets.stanford.edu/StanfordMoocPosts/ | Require submitting request to Stanford University |
| [140] Dataset of LinkedIn profiles of company employees | https://www.reddit.com/r/dataisbeautiful/comments/25qips/how_many_employees_are_moving_between_companies_oc/6yv6lg/ |
| [141], [142], [156] Web Scrapped Video Dataset from different MOOCs (Coursera & edX) | Closed |
| [143] NPTEL MOOC dataset (Finite State Methods for Morphology*, from the Natural Language Processing (NLP) Course. | Closed |
| [144] Image Dataset with 1000 image frames having 200 images per each style. | Closed |
| [127] Dataset from Physics course on edX, containing 4,763 learners and 1,869,406 learner actions [177]. | Closed |
| [151] Muhammad School of Engineers Forum | Closed |
| [152] MOOC platform dataset of three courses offered by the Chinese Universities, including “Microeconomics”, “Finance” and “Introduction to Programming II in C Language” offered on https://www.icourse163.org/ | Closed |
| [153] Data of 100 people to simulate real user test by collecting their operational behavior from a system log file | Closed |
| [157] Learner communication data from Southwest University data (December 2016 to June 2018). | Closed |
| [159] Khan Academy, Udemy and edX | Closed |
| [162] XuetanX MOOC platform | Closed |
| [163] Coursera 2399 courses and 3981 course skills | EMAIL to wcyyao@ustc.edu.cn for the data. |
| [164] Canvas Network dataset from Harvard and MIT | https://dataverse.harvard.edu/dataversion/xxjh |
| [167] COCO dataset: A semantically rich data of online courses [178] | Permission from the authors of [178] required |
| [168] Dataset consisting of large number of MOOC resource experiment objects | Can be obtained by request to author |
| [170] Web crawled dataset from Coursera and Vietnam job data | Closed |
exploitation SPARQL queries on remote servers that contained reusable vocabularies.

Personalized learning is further exploited by using learning analytic techniques. These techniques analyze the learning styles that can be used for classification. In this regard, Mothukuri et al. [94] used agents to workout learning styles of the learners by analyzing course progress patterns. In the same way, Harrathi et al. [120] proposed rules based recommendation system by incorporating resource classification based on blooms taxonomy and by categorizing different forms of activities. Correspondingly, Zhang et al. [122] proposed MCRS using Hadoop and Spark, a distributed computational framework based on association rule mining algorithm which exploited multi-score data analysis to provide personalized learning path to the learner.

Additionally, learning path combination recommendation based on learning network (LPCRLN) was proposed by Liu and Li [148], which categorized the learners into different types based on the course network and learner network. The course network and learner networks were based on characteristics of the learners and courses. Similarly, in Felder & Silverman [181], learning styles combined with and topic modeling [182] were utilized in different studies. Likewise, Aryal et al. [141] mapped learning styles with video styles to provide personalization of MOOC to the learner. Similarly, Hilmy et al. [142] analyzed discussion forums to identify how learners feel about the learning platform and used it as recommendation metric. In the same way, Sankalpa et al. [156] described recommendation based on learner learning styles and preferred video style and categorized the courses for recommendations. Moreover, the VERK learning model was used by Fazuludeen et al. [144] to provide a personalized learning path by mapping learning styles with lecture video styles, course reading material and quizzes.

Machine learning algorithms were also seen in action in the literature. Intayoad et al. [98] exploited k-nearest neighbor and decision trees in context aware recommender systems to classify different type of learners and recommended learning paths using associative rules. Rababallah et al. [119] used a hybrid filtering technique that combined collaborative filtering with an ontology-based approach. A semantic description of learner was presented by the ontology, and CF was used to generate recommendations. Machine learning algorithms like k-means and Apriori algorithms were used by Vélez-Langs and Caicedo-Castro [129] in order to provide customizable personalized learning paths to learners by mining the learner use logs and using rules that associate similar learners based on their actions. Finally, Son et al. [170] recommended a knowledge based recommender system with genetic algorithm (GA) and ant colony optimization (ACO) algorithms to provide learning path based on the learner’s job and background. A lot of focus is given on this domain, as personalized learning paths can help learners complete courses by following a learning path that is appropriate for them. Further research in this domain can help MOOC platform designers implement robust systems that can provide personalized learning path to the learner for successful completion of the course.

4) PRE-REQUISITE RECOMMENDER

Some learners drop out of the course because they do not fulfill the pre-requisites to the enrolled course and lack the background knowledge necessary to understand the concepts in the course. This leads the learner to frustration and demotivation, and as a result, the learner fails to complete the course. MOOCRS can provide pre-requisite recommendations to the learners so they can understand the enrolled course’s concepts. The literature shows learning analytics [183] being used for pre-requisite recommendations. Pang et al. [115] used explicit feedback from the learner by penalizing the learning score feature in the case of failure in task completion. The pre-requisite objectives were recommended, while on success subsequent objectives were recommended. Further extending their study Pang et al. [123] utilized explicit feedback with collaborative filtering to recommend pre-requisites and subsequent learning paths to the learner using correlation coefficient. The literature shows only three studies in this domain and requires attention. In order for the learner to learn a course easily, pre-requisites and their relationship to learning objectives play important role. MOOC platforms like Coursera, Khan Academy, try to focus more on pre-requisites support for better learning experience [123]. These pre-requisites are generally for all types of learners, but recommending pre-requisites for a specific learner, keeping in view different factors such as objective, learning history, background knowledge etc., is still an avenue yet to be explored, and there is a lot of potential for the researchers in this domain.

5) LEARNING OBJECTIVE (LO) RECOMMENDER

LO identifies what skills, attitude, and knowledge a learner should exhibit when succeeding in a course [184]. We found studies using learning style analytics to achieve LO recommendations. Fasihuddin et al. [56] exploited learners’ interaction patterns with open learning environment to classify users based on their learning styles, generating recommendations based on their learning styles. Dai [75] used latent dirichlet allocation to predict the distribution of the course contents in the knowledge domain and predicted knowledge covered in an unknown syllabus. Similarly, Ndiyae et al. [131] exploited the combination of leaner profile and learner knowledge assessment using trace analysis. Venkataraman et al. [65] utilized aptness score by employing course modeling structure as dynamic petri net [185]. Moreover, Harrathiet et al. [95] proposed hybrid knowledge based approach based on ontology to model learners, learning activities and domain in order to recommend learning objectives. Finally, Singelmann et al. [135] used k-nearest neighbor, logistic regression and support vector using learner data and their habits within MOOC to achieve learning objective recommendations. There is still room for further research in this
type of recommender in MOOC as there is very less work found in the literature.

6) CONTENT RECOMMENDER
This recommender system recommends uniquely tailored content to a learner, using learner information, which fits user skill/background and course objectives for the course enrolled. Studies in the literature used machine learning techniques to achieve content recommendations. Furukawa and Yamaji [87] used free descriptors about the learner to recommend contents. Ji et al. [111] used topic similarity and linguistic difficulty level for content recommendation. Finally, Zhao et al. [112] used video contents and sequential inter topic relationship to recommend contents to the MOOC learner. This recommender has a broad scope, as only three studies have focused on these, and researchers can utilize techniques employed for other similar like e-learning domains to improve this type of recommender system.

7) COURSE RECOMMENDER
This type of MOOCRS is gaining ground among the rest as made clear from the current literature. A course recommender system uses learner’s centric attributes to recommend courses. A number of researchers have put their efforts in course recommenders. Fu et al. [66] used learner characteristics, cognitive level with knowledge structure for collaborative filtering. Likewise, Onah and Sinclair [69] used collaborative filtering on user data. Similarly, Garg and Tiwari [70] exploited implicit data collected from monitoring the learner behavior in MOOC environment. Pang et al. [86] proposed improved collaborative filtering technique called Multilayer Bucketing recommendation on map-reduce (MLBR) to achieve the goal. Content based filtering was used by Campos et al. [159] to recommend courses. Similarly Huang and Lu [104] and Hou et al. [109] both used context sensitive filtering. A knowledge base technique was employed by Ouertani and Alawad [100] for course recommendations. Furthermore, learning analytics were used in Chen et al. [81] using data from UpWork⁷ to recommend relevant courses to the learner. Ontology based techniques in Sammout et al. [64] and Campos et al. [105] were used for course recommendations.

Deep learning techniques were also found in the literature to recommend courses. Tang and Pardos [82] used a time augmented recurrent neural network model, and the same author in an extended study by Pardos et al. [83] used LSTM to recommend courses. Further, Zhang [124] used deep belief networks, Agrebi et al. [125] used deep reinforcement learning, Sakboonyarat and Tantatsanawong [137] used multilayer perceptron, and Wang et al. [154] employed attention based convolution neural networks to achieve the task. Yin et al. [158] used cluster based demographic information, Le et al. [165] used deep matrix factorization with normalization (DMF). Moreover, Khalid et al. [167] proposed a Novel online recommendation algorithm for course recommendation. Hybrid approach in to recommend courses were also found in the literature. Apaza et al. [58] used a top-k method with max cost flow, Yanhui et al. [62] and Mohamed [97] proposed content-based filtering with collaborative filtering, Estrela et al. [80] utilized user profile, user similarity, and their combination. Finally, K-NN clustering with content-based filtering was proposed by Cao et al. [149] to recommend courses.

The aforementioned studies and research show the contributions in course recommenders, but there is still room for more in this domain. Future researchers can exploit more techniques and algorithms for improved recommendations and can use base models for benchmarking their solutions.

8) RESOURCE RECOMMENDER
This RS recommends different MOOC learning resources, such as books, videos, lecture-notes, web sites, as per user requirements. Studies show resource recommendations using collaborative filtering techniques. For instance, He et al. [89] used Item-based filtering and user-based filtering combined to achieve resource recommendation for social work training. Similarly, resource recommendation was achieved using item-based collaborative filtering by Lu and Xia [147], while Wang et al. [153] recommended videos. Learning analytics were used by Li and Mitros [63] showing how learners could collaborate by improving resources for remediation. Similarly, Pang et al. [117] proposed a solution using recommendations based on learner neighbor and learner series (RLNLS). An open educational resource (OER) recommender system was proposed by Haji et al. [130] that could be plugged in an OLE to provide resource recommendations. Ndiyae et al. [131] proposed an automatic analysis of learner’s response with knowledge tests to provide personalized recommendation for each learner. Similarly, the use of ontology-based techniques is evident in the literature. Maran et al. [67] represented an ontology network to reuse concepts defined in other ontologies and validated their network using UPON methodology. Moreover, Huang [74] proposed a book resource recommendation system using a library classification ontology based method to recommend books by classifying them into groups. Shapulta et al. [90] proposed a MOOC based OER system (MORS) which recommended OERs to the learners by modeling the MOOC

⁷https://www.upwork.com
and creating process to query OERs. Faqhi et al. [136] simulated the needs of a producer who is searching for educational resources and then used Euclidian distance to measure similarities.

Machine learning techniques were also adopted for resource recommendation in the literature. Hmedna et al. [72] classified learners into groups based on learning styles using supervised learning in order to provide learning contents to the learner. Shaptala et al. [92] used VSM with cosine distance, Chakraborty et al. used clustering and k-means [106], and Cooper et al. used sequential pattern mining [116] for resource recommendations. Similarly, Chang et al. [73] used watch time log for video recommendation. Context-aware factorization machine algorithm was proposed by Chanaa and Faddouli [134] to recommend resources. Similarly, Nangi et al. [143] used a concept similarity network along with a natural language processing technique for learning resource recommendations. Furthermore, Jiang and Pardos [127] used recurrent networks to recommend quiz page. While Tripathi et al. [146] used EmoWare, an emotionally intelligent video recommendation engine with context-aware collaborative filtering approach for videos recommendations. Zhang et al. [96] proposed restricted Boltzmann machines, while Liu et al. [157] proposed the Elmo model to recommend learning resources. Knowledge concept recommendations was achieved by Gong et al. [162] using an end-to-end neural network. Lastly, a hybrid approach using collaborative filtering and time-series approach was used by Pang et al. [114], while a correlated pattern technique was used by Li and Li [88] that combined user-cluster with course-cluster was used to achieve the recommendations. The literature shows work done in resource recommendations, and still there is room for improvement as resources cover wide range. Learning resources in MOOCs can be a book, a chapter, a video clip, topic, a website or any resource that can help learner complete their course and thus there are still lot of opportunities in this recommender for the researchers for improvements.

9) SOCIAL RECOMMENDER

This recommends threads, peers, other learners who can interact with the learner. These can be simple RS or reciprocal RS. Reciprocal RS performs user-user recommendations rather than item-user [186], as it is a two way RS, so it has its own complexities. Collaborative filtering was commonly adopted in literature for social recommenders as Yang et al. used it to recommend discussion threads to the learner [60], while Prabhakar et al. [99] used it to recommend peers with reciprocal RS. Learning analytics was adopted by Labarthe et al. and used chat modules to recommend contact [79], Bouchet et al. [85] insisted on using learner background information while Elghomaly and Bouzidi [138] used trust based model to recommend learner peers. Thomas sampling was implemented by Williams et al. [77] to recommend emails, Mi and Faltings [101] used context tree to recommend discussion forum. Moreover, support vector machines and random forest were utilized in Babinec and Srba [84] for tag recommender, Bouzayane and Saad [121] utilized dominance-based rough set approach (DBRSA) to recommend learner leader (mentor). Furthermore, Gusmão et al. [166] presented a model of a custom forum activity that uses the ontology of tags to classify posts. Similarly, Lan et al. [132] proposed point process while Zhang et al. [152] used self-attention mechanism for thread recommendation, while Yang et al. [61] used an adaptive matrix factorization approach combined with content level modeling. Furthermore, Campos et al. [105], Rahma and Kounteair [139] proposed random forest to recommend forum answers. Similarly, Touimi [151] developed an answering chatbot that recommends answers in a discussion forum using knowledge-based filtering. Finally, Deep learning was used in Yang et al. [59] to recommend top-n discussion forums and Yang et al. [103] for a social recommendation. With rising trends of natural language processing and deep learning algorithms and models, there is still lot of work that can be done to improve social recommender systems.

A clear and precise view of the research and studies conducted for all the types of recommenders are mentioned in Table 10. It can be seen there that most studies are performed on course recommendations followed by resource recommendation and social recommendation. There is lot of room for research in the area of adaptive learning, content recommendation, learning objective recommender and pre-requisite recommendation for the future researchers.

### TABLE 10. Types of MOOCRS found in literature.

| Studies | Recommender          |
|---------|----------------------|
| [55, 57, 58, 62, 64, 66, 68-70, 76, 80-83, 86, 91, 93, 97, 100, 104, 105, 108, 109, 113, 118, 124, 125, 137, 145, 149, 154, 155, 158, 159, 163-165, 167] | Course recommender |
| [71, 169] | Adaptive Learning |
| [87, 111, 112] | Content Recommender |
| [56, 65, 75, 95, 135] | LO recommender |
| [78, 110, 128, 150, 160] | MOOC recommender |
| [94, 98, 102, 107, 119, 120, 122, 126, 129, 133, 140-142, 144, 148, 156, 161, 170] | Personalized learning |
| [115, 123] | Pre-requisite recommender |
| [63, 67, 72-74, 88-90, 92, 96, 106, 114, 116, 117, 127, 130, 131, 134, 136, 143, 146, 147, 153, 157, 162, 168] | Resource recommender |
| [59-61, 77, 79, 84, 85, 99, 101, 103, 121, 132, 138, 139, 151, 152, 166] | Social recommender |

C. RQ3. WHAT TECHNOLOGIES AND TECHNIQUES ARE USED TO IMPLEMENT MOOCRS IN THE LITERATURE?

There are many techniques and technologies that were found in the literature; however, we have classified them into 9 categories as follows:

1. Collaborative filtering
2. Content-based filtering
3. Knowledge Based filtering
4. Context Sensitive filtering
5. Ontology based filtering
6. Learning analytics
7. Machine learning
8. Deep learning
9. Hybrid approach

In this section, we shall discuss each technique used in the literature.

1) COLLABORATIVE FILTERING (CF)
This approach relies on a user’s behavior or user rating for items. It is based on similar ‘users’ to recommend content [187]. The advantage of using these filters is that no domain knowledge is required, and they provide serendipity where users discover new interests during recommendations [188]. Using learner profile, these systems can use personal information, previous activities, and behavior to find learners with similar preferences and recommend learning resources/materials accordingly [189]. These algorithms recommend a list of top-N items or find prediction ratings. The literature shows that Fu et al. [66] and Bousbahi and Chorfi [68] recommended courses using nearest neighbor techniques, while Pang et al. [86] used it along with LSH and MinHash. Garg and Tiwari [70] used explicit feedback from the learner and Onah and Sinclair [69] implemented a collaborative framework in python to achieve the goal. Similarly, Venkataraman et al. [65] used Bayesian networks to recommend learning objectives. A collaborative filtering approach was used by Pang et al. [115] to recommend pre-requisite and subsequent learning objects based the forgetting-punished technique and similarly in another study, Pang et al. [123] used the learner’s location (progress) in the course for appropriate recommendation. Further, resource recommendation was achieved using item-based collaborative filtering by Lu and Xia [147], while item-based filtering and user-based filtering combined was utilized by He et al. [89]. Similarly, Hmedna et al. [72] used supervised learning by classifying learners into different learning styles. Furthermore, Zhao and Liu [153] utilized vector spatial model (VSM) to recommend top-n relevant videos. Social recommendation like peer recommendation was achieved using similarity matrix in Prabhakar et al. [99]. MOOC thread recommendation was accomplished using adaptive feature-based matrix factorization by Yang et al. [60]. Lastly, Wang et al. [102] used multivariate weight algorithms, and bipartite graph context was used by Xiaoyan and Jie [126] to achieve personalized learning recommendations. Collaborative filters have a drawback, they cannot handle a new user with no historical data. This is known as a ramp-up/cold start problem [188]. These filters require a large amount of data initially, and it is useless if it contains a small rating base. Further, the number of rating items associated with the user affects the system’s accuracy [190]. Table 11 shows the summary of the studies found based on collaborative filtering techniques in the literature.

2) CONTENT-BASED FILTERING (CBF)
These systems try to recommend items based on matching contents or preferences in a user profile with the item’s attributes [191]. These models do not rely on other users’ data, as recommendations are specific to a target user, and it can capture the user’s particular interests. Huang and Lu [104] utilized content-based filtering to recommend top-n video resources using mean average precision with base line work (popularity, direct content match and classical matrix factorization), while discussion forum recommendation was achieved by Yang et al. [61] using an adaptive matrix factorization approach combined with content level modeling, and Campos et al. [159] proposed non negative matrix factorization (NMF) to find similarities between users for content based filtering. As the features/content of items are hand-engineered, the technique requires domain knowledge to an extent. Content-based filtering model has limited expansion capabilities as it is based on existing user interests [192]. Further, these filters also have a cold-start problem and require many ratings to recommend [193]. Table 12 shows the summary of the studies found based on content-based filtering techniques in the literature.

3) KNOWLEDGE-BASED FILTERING (KBF)
This technique uses a knowledge base to store knowledge about the user and item. Explicit feedback is collected from the user using a dialogue-based interface, and the knowledge base is updated accordingly [41]. Ouertani and Alawadh [100] used knowledge-based recommender systems to recommend courses. Toumi et al. [151] used latent
elements for recommendation. Raghuveer et al. [109] employed an online learning algorithm to collect data for course recommendations with big data support using contextual hierarchal tree algorithms. The study proposed dissimilarity amongst the courses to handle huge datasets and to overcome the problems of traditional approaches. Assami et al. [107] highlighted seven main criteria that represent a learner’s choice and source of motivation that can be used in a suggested recommendation model. Faqhi et al. [136] simulated the need for a producer who is searching for educational resources and then used Euclidean distance to measure similarities. Assami et al. [140] confers that a learner profile is limited if MOOC platforms are used to gather information, insisting on gathering information from social professional networks to enrich learner information for efficient recommendations. Assami et al. [133] used trace-based approach to extract user data and content data and stored them in structured form in a learning ontology database. Moreover, the same author in another study [150] presented a model of a custom forum activity for the MOOC platform that recommended contents and users by using the ontology of tags to classify posts. Furthermore, Sebbaq et al. [160] used semantic web, linked open data, and ontology modeling to recommend a MOOC platform to assist the teachers in preparing lectures and to overcome the problems of traditional approaches. Finally, González-Castro et al. [169] used ontologies to recommend video fragments to the learners. Table 15 shows the summary of the studies found based on ontology-based filtering techniques in the literature.

5) ONTOLOGY-BASED FILTERING
Ontology is the branch of metaphysics that focuses on the study of existence, by studying the world’s structure and by discovering the entities and types of entities. The study of ontology can be traced back to Plato and Aristotle [194]. Ontology describes concepts explicitly and represents them in a knowledge base. A number of studies were found that used an ontology-based approach to model the MOOC elements for recommendation. Raghveer et al. [57] used the semantic structure of the courses and constructive reward based learning algorithm to recommend learning objectives.

6) LEARNING ANALYTICS
Learning analytics is an educational data mining measure that uses data mining techniques to collect and

Table 12. Studies based on content-based techniques.

| Ref. | Model | Recommender | Evaluation Metric |
|------|-------|-------------|-------------------|
| [61] | Adaptive Matrix Factorization approach | Forum | Mean Average Precision |
| [104] | Top-N Course Recommender | Course | Precision |
| [159] | Topic modeling with non-negative matrix factorization | Course | Mean Coherence |

Table 13. Studies based on knowledge-based filtering.

| Ref. | Model | Recommender | Evaluation Metric |
|------|-------|-------------|-------------------|
| [100] | MOOC Recommendation Portal | Course | Not mentioned |
| [151] | LDA and Bayesian statistical methods | Social | Similarity |
| [170] | Genetic Algorithm, Ant Colony Optimization Algorithm | Personalized learning path | Objective values |

Table 14. Studies based on context-sensitive filtering.

| Ref. | Model | Recommender | Evaluation Metric |
|------|-------|-------------|-------------------|
| [98] | K-nearest Neighbor (KNN), Decision Tree Association Rules | Personalized Learning Path recommendation | Accuracy |
| [109] | Contextual Hierarchal Tree algorithm | Course | Average Reward and Average Regret |

Sammour et al. [64] and Campos et al. [105] used linked open data (LOD) to create an ontology-based recommender system for web-based MOOCs to achieve effective personalized learning. Maran et al. [67] represented an ontology network to reuse concepts defined in other ontologies and validated their network using UPON methodology. Moreover, Huang [74] proposed a book resource recommendation system using library classification ontology-based method to recommend books by classifying them into groups. Piao and Breslin [78] used dataset collected from LinkedIn to compare different modeling techniques such as skill-based, job-based, and education-based user modeling strategies, showing that skill-based modeling performs better than the other two. Shaptala et al. [90] proposed a MOOC-based OER system (MORS) which can recommend OERs to learners by modeling the MOOC and created a process to query OERs. Assami et al. [107] highlighted seven main criteria that represent a learner’s choice and source of motivation that can be used in a suggested recommendation model. Faqhi et al. [136] simulated the need for a producer who is searching for educational resources and then used Euclidean distance to measure similarities. Assami et al. [140] confers that a learner profile is limited if MOOC platforms are used to gather information, insisting on gathering information from social professional networks to enrich learner information for efficient recommendations. Assami et al. [133] used trace-based approach to extract user data and content data and stored them in structured form in a learning ontology database. Moreover, the same author in another study [150] presented a functional architecture for MOOC recommendation by utilizing ontological representation of the learner model and MOOC contents for intelligent suggestions. Moreover, Gusmão et al. [166] presented a model of a custom forum activity for the MOOC platform that recommended contents and users by using the ontology of tags to classify posts. Furthermore, Sebbaq et al. [160] used semantic web, linked open data, and ontology modeling to recommend a MOOC platform to assist the teachers in preparing lectures and to overcome the problems of traditional approaches. Finally, González-Castro et al. [169] used ontologies to recommend video fragments to the learners. Table 15 shows the summary of the studies found based on ontology-based filtering techniques in the literature.
TABLE 15. Studies based on ontology-based filtering.

| Ref. | Model                                  | Recommender       | Evaluation Metric                  |
|------|----------------------------------------|-------------------|------------------------------------|
| [57] | Semantic modeling of Courses           | Course            | Reward                             |
| [64] | Linked Open Data                       | Course            | Not mentioned                      |
| [67] | Ontology network by linking ontologies | Resource          | UPON methodology                   |
| [74] | Library Classification Ontology        | Resource (Books)  | Similarity                         |
| [78] | User Modeling                          | MOOC              | Success @ rank N/ Means Reciprocal Rank (MRR) |
| [90] | MOOC Modeling                          | Resource (Learning Resources) | Not Mentioned |
| [95] | Hybrid Approach                        | Learning Objective | Not Mentioned                      |
| [105] | Link open data is used with collaborative filtering | Course | Not Mentioned |
| [107] | Ontology Modeling                      | Personalized Learning | Not Mentioned |
| [136] | Ontology                              | Resource (Learning Resources) | Euclidian distance |
| [140] | Social Media Mining (SMM)              | Personalized Learning | Euclidian distance |
| [133] | Trace Based Approach                   | Personalized Learning | Not Mentioned |
| [150] | Learner Ontology                       | MOOC              | Not Mentioned                      |
| [166] | Ontology of tags to classify posts     | Course expert recommender in discussion forums | Not Mentioned |
| [160] | Semantic web and Ontology              | MOOC Recommender for teachers | Not Mentioned |
| [169] | Ontological structures                 | Video fragment recommender | Not Mentioned |

analyze data in order to understand and improve learners’ quality of learning [183]. The term “learning style” refers to how an individual concentrates on processes, internalizes, and retains new and challenging information [9]. “A learning style is a habitual and unique behavior of acquiring skills and knowledge through study or experience” as defined by Smith & Dalton [10]. We found the use of Learning analytics in the literature for recommendations. Fasihuddin et al. [56] proposed an idea for an adaptive model to personalize the open learning environment based on the Felder & Silverman learning style model [11]. Li and Mitros [63] showed how learners could collaborate by improving resources for remediation. Hmedna et al. [71] proposed a recommender system that used explicit feedback from learners by using concept-based questionnaires mapped to learning concepts. Dai et al. [75] proposed a recommender system for effective path of learning objects for an individual learner. Labarthe et al. [79] designed a recommendation system to suggest relevant chat contacts using learner progress and demographic data. Chen et al. [81] proposed a system that collected tasks from UpWork8 and recommended them to the learner and monitor learners progress on tasks. Bouchet et al. [85] established that peer recommender systems improve learner engagement and investigated the difference between recommendation strategies. Furukawa and Yamaji [87] proposed an adaptive recommendation of teaching material to the learner by analyzing free descriptors. Muthukuri et al. [94] proposed a feedback capturing agent to analyze learner styles by monitoring learner progress to update cognitive profile of the learner in order for effective recommendation. Pang et al. [117] proposed a solution using recommendation based on learner neighbor and learner series (RLNLS). Harrathi et al. [120] used Bloom’s taxonomy to classify learners into different learning styles in order to recommend learning material. Zhang et al. [122] used Multi-Grained-BKT and Historical-BKT, two knowledge tracing models to evaluate learning state to recommend learning material to the students identifying their weak points. A MOOC based open educational resource (OER) recommender system was proposed by Hajri et al. [130] that could be plugged in an OLE to provide recommendation of OER to the learner. Ndiyae et al. [131] proposed an automatic analysis of learner’s response with knowledge tests to provide personalized recommendation for each learner. Elghomary and Bouzidi [138] proposed a dynamic peer recommendation model to suggest learning partners based on their needs and behaviors using a trust model system (TMS). Finally, a learning network based learning path combination recommender method LPCRLN was employed by Liu and Li [148] to analyze learning relation between the course and learner by creating network of courses and learners to propose recommendations. Table 16 shows studies that used learning analytics for recommendations.

7) MACHINE LEARNING (ML)
ML algorithms mimic the human brain by acquiring knowledge through training and learning. ML algorithms have different categories including supervised, semi-supervised, k-nearest neighbor, transfer, reinforcement and active learning. As recommendation problems can form a generalization of the ML classification, ML algorithms can be used efficiently to solve those problems [195]. For example, text rank is used for content recommendation by Ji et al. [111], tf-idf for recommendation by Zhao et al. [112], K-means and Associate Rule Mining are used for course recommendation by Aher and Lobo [55] and Fauzan et al. [164]. Similarly, Song [76] used Machine Factorization, Su et al. [91] used big data analytics, Jain [108] utilized random forests, classification tree, k-nearest neighbors, and logistic regression. Along with that, Wang et al. [93] used clustering techniques, Zhang et al. [113] utilized improved apriori algorithm, [145] Xia used vector space model (VSM), and finally Mondal et al. [155] used data mining techniques to achieve course recommendations.

Machine learning algorithms have also played role in social recommendation as Williams et al. [77] used Thomas sampling for email recommendation, Rahma and Kouthe air [139] proposed random forest for forum answer recommendation, [https://www.upwork.com/](https://www.upwork.com/)
while Bouzayane and Saad [121] utilized dominance-based rough set approach (DBRSA) for leader recommendation. Similarly, Mi and Faltings [101] used context tree for MOOC forum recommendation, Lan et al. [132] proposed point process and Zhang et al. [152] used self-attention mechanism for thread recommendation. Apart from that, ML algorithms are adopted for Learning resource recommendation as well. Yao et al. [163] used LDA, while Nangi et al. [143] used concept similarity network along with natural language processing techniques. LDA was also used to achieve MOOC recommendation by Zarra et al. [110], while k-mean clustering in Li et al. [118], and context-aware factorization machine algorithm were used by Chanaa and Faddouli [134] in a personalized learning path. Furthermore, resource recommenders using machine learning included tag recommender using support vector machines, and random forest were utilized by Babinec and Srba [84], VSM with cosine distance by Shaptala et al. [92]. Furthermore, clustering and k-means for learning resource in Chakraborty et al. [106],

Cooper et al. [116] utilized sequential pattern mining and Chang et al. [73] used watch time log for video recommendation. Finally, Khalid et al. [167] used the concept of hyperspheres with voting to generate course recommendations. The summary of studies based on machine learning algorithms are shown in Table 17.
TABLE 18. Studies based on deep learning.

| Ref. | Model | Recommendation | Evaluation Metric |
|------|-------|----------------|------------------|
| [59] | Constructivist Reward Based Learning Algorithm | Top-N Learning Discussion Recommendations | Objective Function Comparison |
| [82] | LSTM / TLSTM (Time Augmented LSTM) | Personalized Course recommendation | Accuracy |
| [83] | LSTM | Personalized Course Navigation | Accuracy |
| [96] | Restricted Boltzmann Machines | Resource (Learning Resources) | Accuracy |
| [103] | RNN | Social | Support |
| [116] | Sequential pattern mining | Resource (Video) | Support / Confidence |
| [125] | Markov Decision Process | Personalized Course | Precision / Recall |
| [124] | n deep belief networks (DBNs) | Course Recommender | RMSE |
| [137] | Multilayer Perceptron | Course Recommender | Accuracy |
| [146] | LSTM | Resource (Video) | RMSE |
| [127] | Recurrent Networks | Resource (Quiz Page) | Accuracy |
| [154] | Attention based CNN | Course Recommendation | Not Mentioned |
| [157] | ELMo Model/ Wide & Deep networks | Resource (Learning Resources) | Accuracy |
| [162] | End-to-end graph neural network-based approach | Resource recommender (Concept Knowledge) | Hit Ratio / nDCG, Mean Reciprocal rank |
| [165] | Deep Matrix Factorization | Course | nDCG |

TABLE 19. Studies based on hybrid approach.

| Ref. | Model | Recommend ation | Evaluation Metric |
|------|-------|----------------|------------------|
| [58] | Top-K Method, Max-Cost Flow, Submodular Method | Course | Accuracy |
| [62] | Collaborative and Content based filtering using historical information | Course | nDCG, F-Score |
| [80] | User Profile, User Similarity and Combination of both | Course | Not Mentioned |
| [88] | Correlated pattern-based recommendations | Resource (Learning Resources) | Pearson Similarity |
| [97] | Collaborative and Content Based Filtering | Course | Not Mentioned |
| [114] | Collaborative Filtering and Time Series | Resource | MAE, MRE |
| [119] | Ontology + Collaborative Filtering | Personalized Learning Path (MOOCs) | Cosine Similarity |
| [128] | Hybrid (Collaborative Filtering/ Machine learning) | MOOC | RMSE, MAE |
| [135] | k-nearest neighbors, logistic regression, and support vector machines | Learning Objective | Not Mentioned |
| [129] | K-Mean, Apriori Algorithm | Personalized Learning | Not Mentioned |
| [141] | VGG16 Videos classified according to learning analytics | Personalized Learning | Error |
| [142] | VGG16, VGG19, Inception V3, with user sentiment as additional feature | Personalized Learning | Not Mentioned |
| [144] | Inception V3 and MobileNet V2 and Course Mapping using VARK learning model [187] | Personalized Learning | Error |
| [149] | K-NN clustering and content-based approach | Course | Accuracy |
| [156] | RestNet50, VGG16m VGG19 | Personalized Learning | Accuracy, loss |
| [158] | LDA with Collaborative Filtering | Course | Mean Reciprocal Ranking |
| [161] | Ontology based approach combined with collaborative and content-based filtering | Personalized learning | Not Mentioned |
| [168] | Collaborative filtering with deep learning | Resource Recommendation | Accuracy, RMSE, MAE |

8) DEEP LEARNING (DL)

Deep learning is enjoying massive hype in the research industry. The past decade has witnessed a tremendous success of deep learning in many application domains. Recently deep learning has been changing the recommendation architecture dramatically and improving performance. The literature shows the implementation of deep learning in different recommenders. Sakboonyarat and Tantatsanawong [137] used multilayer perceptron for course recommendation. Similarly, Zhang et al. [124] proposed a course recommendation model MOOCRC based on deep belief networks (DBNs). Likewise, Pardos et al. [83] used LSTM to recommend course navigation. Further Tang and Pardos [82] used LSTM with time augmentation, and Agrebi et al. [125] proposed Markov decision process for course recommendation. Moreover, Le et al. [165] used deep matrix factorization, and Wang et al. [154] used attention-based convolution neural networks for course recommendation.

Resource recommendation was achieved by Zhang et al. [96] using restricted Boltzmann machines, and Liu et al. [157] proposed Elmo model to recommend learning resources. Similarly an end-to-end graph neural networked-based approach was used in Gong et al. [162] to recommend concept knowledge, Jiang and Pardos [127] used recurrent networks to recommend quiz pages, and Cooper et al. [116] employed LSTM to recommend videos.

Social recommenders using deep learning were achieved used RNN by Yang et al. [103], and reinforcement learning was used to recommend top-N discussion forums by Yang et al. [59]. Table 18 shows summary of the studies that utilized deep learning approach for recommendation.

9) HYBRID FILTERING

Every recommender system has its strengths and weaknesses. Keeping in view this fact, the researchers have combined multiple recommendation techniques to take advantage of their strengths combined [193]. Chao et al. used SVD with Restricted Boltzmann algorithms to recommend MOOC resources [128]. Similarly, course based recommender system proposed by Li and Li [88] utilized correlated pattern-based recommendations that combines MOOC clusters (course based cluster and user based cluster)
with collaborative filtering. Likewise, time series used for resource recommendation was adapted by Pang et al. [114]. Collaborative filtering combined with an ontology-based approach was used by Rabahallah et al. [119] and Slimani et al. [161] to achieve personalized learning. Likewise, k-mean and apriori algorithms were used by Vélez-Langs and Caicedo-Castro [129]. Deep learning techniques combined with learning analytics in were utilized by Aryal et al. [141] and Hilmy et al. [142] for personalized learning. K-NN clustering with a content-based approach was proposed in Cao et al. [149] while a top-k method with max cost flow by Apaza et al. [58] for course recommendation. Similarly, content-based filtering and collaborative filtering proposed by Yanhui et al. [62] and Mohamed [97]. Further, user profiles, user similarity and their combination were used in Estrela et al. [80] for course recommendations. Moreover, LDA in combination with collaborative filtering was utilized by Yin et al. [158] to recommend courses. Finally, Wu [168] proposed collaborative filtering approach based on deep learning technique that used spark architecture by employing embedding vectors with Laplacian matrix to achieve the resource recommendation. Table 19 shows detailed information of the model used based on hybrid approach with their recommendation type and the evaluation metric used.

The studies are classified according to the techniques used in order to give a clear picture of the literature and help the reader. Table 20 shows the studies grouped categories. The literature clearly shows that the machine learning techniques are used in most studies followed by learning analytics, ontology based, deep learning, hybrid approaches and collaborative filtering techniques. With the rise of popularity in deep learning techniques in multimedia, there is still a tremendous scope using deep learning with learning analytics and ontology-based approaches to create intelligent hybrid recommender systems for MOOC.

### D. RQ4. WHAT WERE THE EVALUATION METRICS USED TO EVALUATE THE EXPERIMENTS IN THE LITERATURE?

Most of the papers selected for this study mentioned experiments and evaluation metrics depending on the nature of the experiments. Table 21 shows a list of evaluation metrics used in different studies in the literature.

From the data in Table 21, it is evident that accuracy, precision, recall, f-score are used in most of the experiments. This information will help future researchers to see which...
TABLE 22. Country-wise frequency of published articles.

| Country         | Studies | Total |
|-----------------|---------|-------|
| Algeria         | [119]   | 1     |
| Australia       | [56]    | 1     |
| Brazil          | [105, 159, 166] | 3 |
| Canada          | [99]    | 1     |
| China           | [62, 66, 74, 76, 86, 88, 89, 96, 102, 104, 113-115, 117, 118, 122-124, 126, 128, 145, 147-149, 152-154, 157, 158, 163, 168] | 31 |
| Colombia        | [129]   | 1     |
| France          | [79, 85, 90, 121, 125, 130] | 6 |
| India           | [55, 57, 65, 70, 94, 108, 143, 146, 155] | 9 |
| Indonesia       | [164]   | 1     |
| Ireland         | [78]    | 1     |
| Japan           | [75, 87] | 2     |
| Jordan          | [64]    | 1     |
| Morocco         | [72, 97, 107, 110, 133, 134, 136, 138, 140, 150, 151, 160, 161] | 13 |
| Netherlands     | [81]    | 1     |
| New Zealand     | [167]   | 1     |
| Peru            | [58]    | 1     |
| Portugal        | [80]    | 1     |
| Saudi Arabia    | [68, 100] | 2     |
| Senegal         | [131]   | 1     |
| Slovakia        | [84]    | 1     |
| South Korea     | [111]   | 1     |
| Spain           | [71, 169] | 2     |
| Sri Lanka       | [141, 142, 144, 156] | 4     |
| Switzerland     | [101]   | 1     |
| Taiwan          | [73, 91, 93] | 3     |
| Thailand        | [98, 137] | 2     |
| Tunisia         | [95, 120, 139] | 3     |
| UK              | [69]    | 1     |
| Ukraine         | [92]    | 1     |
| USA             | [59-61, 63, 67, 77, 82, 83, 103, 106, 109, 112, 116, 127, 132, 135, 162] | 17 |
| Vietnam         | [165, 170] | 2     |

metrics is used sparingly and they can compare their research using evaluation for benchmarking and they can refer to the related studies to see how the experiments were evaluated and how they can be improved.

E. RQ5. WHICH COUNTRIES ARE INVOLVED IN MOOCRS RESEARCH?

The literature studied had a maximum of 31 papers from China, followed by 17 from the USA, 13 from Morocco, 9 from India, 6 from France, and 4 from Sri Lanka, 3 each from Brazil, Spain, Taiwan, and Tunisia, followed by Japan, Thailand, Vietnam and Saudi Arabia with 2 papers each. Algeria, Australia, Canada, Columbia, Ireland, Netherlands, Peru, Portugal, Senegal, Slovakia, South Korea, Spain, Switzerland, UK, Ukraine, and Jordan had 1 paper each in the literature. Details of papers with references and respected country details are in Table 22.

This information can help researchers show which countries lack research in this domain and what are the possible avenues they can target in those countries to start research in this domain. On the contrary this information can help researchers study the dynamics of why a certain country is progressing in this domain and what resources, datasets, funding agencies, or government to target when they want to excel in this domain.

F. RQ6. WHAT ARE THE POPULAR TRENDS BASED ON TECHNOLOGIES USED AND TYPE OF RECOMMENDATION IN MOOCRS?

In this study, we found the trends in technologies shown in Table 20 and MOOCRS types shown in Table 10. Over the years, machine-learning algorithms have been widely used, with 27 articles, 16 studies focused on collaborative filtering techniques, 16 studies each in learning analytics and ontology-based techniques, 18 studies highlight hybrid approaches. Similarly, deep learning was used in 15 studies, and context-sensitive, content-based, and knowledge-based recommender systems used in 3 articles. According to this

TABLE 23. Number of funded studies in each country.

| Country          | Studies | Funded Studies in MOOCRS |
|------------------|---------|--------------------------|
| Brazil           | [105]   | [159] [166] 3            |
| China            | [89, 96, 102, 113-115, 118, 122-124, 126, 128, 145, 152, 158] | 15 |
| France           | [85]    | 1                        |
| India            | [94]    | 1                        |
| Ireland          | [78]    | 1                        |
| Japan            | [75]    | 1                        |
| Netherlands      | [81]    | 1                        |
| Slovakia         | [84]    | 1                        |
| South Korea      | [111]   | 1                        |
| Spain            | [169]   | 1                        |
| Sri Lanka        | [141, 142] | 2                     |
| Taiwan           | [73, 91] | 2                        |
| Thailand         | [137]   | 1                        |
| UK               | [69]    | 1                        |
| USA              | [59-61, 82, 83, 103, 127, 162] | 8     |
| Vietnam          | [165]   | 1                        |
data, machine learning, collaborative filtering, ontology-based techniques, learning analytics, and hybrid approaches are trending, whereas deep learning has lots of potential in this domain and is slowly gaining popularity in the field. Context-sensitive, content-based, and knowledge-based methods were less popular amongst the MOOCRS research community. Figure 5(a) and Figure 5(b) show the trend of technologies over the years.
### TABLE 24. Studies and their funding/supporting agencies.

| Ref. | Country | Agency |
|------|---------|--------|
| [59] | USA     | “Funded in part by NSF grants IIS-1320064” |
| [60] | USA     | “Supported in part by NSF grants IIS-1320064 and OMA-0836012” |
| [69] | UK      | “Funded by Mr. Adakole, S. Onah” |
| [75] | Japan   | “Supported by JSPS KAKENHI Grant Number 15K00423 and the Kayamori Foundation of Informational Science”. |
| [73] | Taiwan  | “Supported by the Ministry of Science and Technology (MOST) and the Ministry of Education (MOE) of Taiwan under grant numbers MOST-104-2622-B-009-001 and MOST-104-3115-E-194-001” |
| [89] | China   | “Financially supported by 2015 annual discipline construction project in philosophy social sciences ‘12th Five-Year Planning of Guangdong Province (GD15XSH05), National Statistical Science Research project of China (No. 2015YFY1), Natural Science Foundation of Guangdong Province China (No. 2014A030313632) and National Natural Science Foundation of China (No. 61375006, 11401223, 61402106)” |
| [81] | Netherlands | The author’s research is supported by the Extension School of the Delft University of Technology. The author’s research is supported by the Leiden-Delft Erasmus Centre for Education and Learning |
| [82] | USA     | “Supported by the National Science Foundation (NSF Award #1547055)” |
| [83] | USA     | “Supported by edX partner’s Research Data Exchange (RDX) program and the support contributed by the edX data team, TU Delft’s Office of Online Learning” |
| [84] | Slovakia | “Partially supported by grants No. APVV-15-0508, VG 1/0646/15, KEGA 028STU-4/2017 and it is the partial result of collaboration within the SCOPES JRP/JP, No. 160480/2015” |
| [91] | Taiwan  | “Supported in part by Research Centre for Advanced Science and Technology, National Central University, Taiwan” |
| [94] | India   | “Supported by Centre for Development of advanced Computing(C-DAC), a scientific society under Ministry of Electronics & Information Technology (MeitY), Government of India” |
| [96] | China   | “Funded by the National Science and Technology Support Program (No. 2015BAAK07B03), and specific funding for education science research by self-determined research funds of CCNU from the colleges basic research and operation of MOE (grant number CCNU17QN0004)” |
| [103] | USA     | “Supported by Zoom In Inc.” |
| [105] | China   | “Supported by Federal Institute of Education, Science and Technology of Rio de Janeiro, DPq/UNIRIO and CAPES, CNPq and FAPERJ (Brazil)” |
| [113] | China   | “Funded by the National Programs for Science and Technology Development (grant number 2015BAAK07B03), the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD), Jiangsu Collaborative Innovation Centre on Atmospheric Environment and Equipment Technology (CICAEET), and specific funding for education science research by self-determined research funds of CCNU from the colleges basic research and operation of MOE (grant number CCNU17QN0004)” |
| [111] | South Korea | “Supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No. R0190-16-2012, High Performance Big Data Analytics Platform Performance Acceleration Technologies Development) and Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2016R1D1A1A09919590)” |
| [78] | Ireland | “Financial support of Science Foundation Ireland (SFI) under Grant Number SFI/12/R2/2289 (Insight Centre for Data Analytics)” |
| [102] | China   | “Supported by the National Natural Science Foundation of China (61572466) and by the Beijing Natural Science Foundation (4162059)” |
| [85] | France  | “Funded by the French Educational Board and by the Human-Cantered Technology Cluster of the University of Sydney” |
| [111] | China   | “Funded by computer science and technology subject of Shanghai Polytechnic University with No. xxkd1604” |
| [118] | China   | “Supported MOST MOST-104-2622-B-009-001, MOST-104-3115-E-194-001, the National Natural Science Foundation of China (61702532) and the Key Program of National Natural Science Foundation of China (61532001, 61432002)” |
| [114] | China   | “Funded by the Subject of Computer Science and Technology of Shanghai Polytechnic University with No. xxkd1604 and financial No. B50NH17HIZ01-41” |
| [122] | China   | “Partially supported by the National Natural Science Foundation of China (NSFC Grant Nos.61472006, 61772039, 61761124) and 61646202” |
| [128] | China   | “Financially supported by Ministry of Education of the People’s Republic of China (Grant No.17YJA80030)” |
| [137] | Thailand | “Supported by Mahidol Wittayanusorn School, Thailand” |
| [145] | China   | “Financially supported by the Key Disciplines of Shanghai Polytechnic University under Grant No. XKKZD1604” |
| [125] | China   | “Funded by computer science and technology subject of Shanghai Poly-technic University with No. xxkd1604” |
| [127] | USA     | “Partly supported by the National Natural Science Foundation of China (71772101/71490724) and the United States National Science Foundation (1547055/1446641)” |
| [141, 142] | Sri Lanka | “Supported by the Administration of Sri Lanka Institute of Information Technology (SLIIT)” |
| [124] | Sri Lanka | “Supported by the National Key Research and Development Program of China (no. 2017YFB1401300, 2017YFB1401304), the National Natural Science Foundation of China (no. 61702211), and the Self-Determined Research Funds of CCNU from the Colleges Basic Research (nos. CCNU17QN0004 and CCNU17GF0002)” |
| [126] | China   | “Fund project: Data Structure and Algorithm Design of Xi’an University of Science and Technology (No.2010216003)” |
| [152] | China   | “Partially supported by National Key Research and Development Program of China with Grant No. 2018AAA0101900 / 2018AAA0101902, Beijing Municipal Commission of Science and Technology under Grant No. Z181100008918005, and the National Natural Science Foundation of China (NSFC Grant No. 61772039 and No.91646202)” |
| [158] | China   | “Partially supported by NSF grant U1866602,61602129, 61772157” |
| [61] | USA     | “Supported in part by NSF grants OMA-0836012 and IIS-1320064” |
| [159] | Brazil   | “Financial support by CAPES, CNPq, and FAPERJ (Brazil)” |
| [166] | Brazil   | “Financial aid provided by CNPq, Brazilian National Council for Technological and Scientific Development” |
| [165] | Vietnam  | “Funded by University of Science, VNU-HCM, under grant number CNTT 2020.05” |
| [162] | USA     | “Supported by NSF under grants IIS-1526499, IIS-1763325, IIS-1909335, CNS-1939041, by Science and Technology Project of the Headquarters of State Grid co., LTD under Grant No. 5700-202055267A-0-0-0, and by NKPs under grants” |
As far as the MOOCRS types are concerned, 38 studies focused on course recommenders, followed by MOOC resource RS with 26 papers. Similarly, personalized learning with 18 papers, social RS systems with 17 and Objective RS with 5, MOOC RS with 5, content RS with 3, pre-requisite RS with 3, and adaptive learning with 3 papers. MOOC recommendations on courses, resources, the social aspect of MOOC, and personalized learning have been the focus of the researchers’ attention. In contrast, pre-requisite and adaptive learning systems are ignored areas in the domain and are a potential scope for future researchers. Figure 6(a) and Figure 6(b) shows trends of MOOCRS publications over the years. Finally, Figure 7(a) and Figure 7(b) show that papers published in journals have increased more than those in conferences. It shows that the increasing researchers’ interest in this domain.

G. RQ7. HOW MANY STUDIES IN THE LITERATURE WERE FUNDED AND BY WHICH FUNDING AGENCY?

We identified around 40 out of 116 studies that were either funded or supported by the public/private research organizations. Details of funding studies and their funding/supporting agencies and country are in Table 23 and Table 24. This information can give future researchers in search of grants a better idea of which country or which funding agency can help them in their research. The data shows China followed by USA have more agencies funding this domain.

IV. CONCLUSION AND FUTURE DIRECTIONS

Online learning environments have gained massive attention since the start of 2020 during the lockdown while the educational industry was surviving on online teaching tools worldwide. MOOC is an e-learning environment that has gained popularity in the last decade but caught attention after the COVID-19 outbreak. MOOC’s success and its learners’ main hurdle is the rising dropout rate, which is caused by the inappropriate selections from the massively available options platforms offer. The issue can be resolved by recommending the right options to the learner to complete the course successfully. Therefore, MOOCRS plays a vital part in the learner’s success and reduces cognitive overload for the learner. Extensive research has been done in this domain in the last decade. Unfortunately, a comprehensive insight of the MOOCRS is not available to help the researchers, students, and practitioners. Therefore, to fill in the literature gap, this is the first mapping survey in this realm. In this study, we categorized the MOOCRS according to the elements they recommend and mentioned the adopted technologies, datasets, and the evaluation metrics used in the literature. Moreover, we have also identified the popular trends in adopting MOOCRS and silent/ignored areas.

This study has covered the research published in last nine years and identified all the potential research areas in this field by highlighting the trending techniques, types of recommendations, datasets, funding agencies, and spatial and temporal aspects of the domain studies. The literature shows that research in past has mostly focused on courses, learning resources and social recommendations. There are very few studies that target recommendations for MOOC developers/teachers and are more focused on MOOC learner. The study concluded that there are tremendous opportunities for the future researchers in the area of learning paths, learning objectives, pre-requisites, content recommendations and adaptive learning, use of learners’ bio-informatic data for recommendations, sub-topic level micro recommendations, cross platform recommendations of resources between different MOOC platforms. One of the main gaps identified in this study was the unavailability of publicly available MOOC dataset. A complete multimedia dataset along with MOOC related social data can help researchers explore the area more dynamically, and MOOCRS can be improved tremendously. This will additionally provide a benchmark for the researchers to improve their results. We have also highlighted potential countries and funding agencies that have supported this domain, as this information can be beneficial for future researchers to target research in countries that lack research in this domain. Technology like Deep Learning and NLP, combined with learning analytics and ontology design, has excellent potential in MOOCRS. It is strongly recommended that these avenues be explored to achieve better benchmarks in the domain. It is believed that the new researchers and practitioners will get the crux of the literature published in the last nine years that this will help them in exploring new research avenues.

REFERENCES

[1] R. B. Duffey and E. Zio, “Analysing recovery from pandemics by learning theory: The case of CoVid-19,” IEEE Access, vol. 8, pp. 110789–110795, 2020.
[2] D. Zhang, J. L. Zhao, L. Zhou, and J. F. Nunamaker, Jr., “Can e-learning replace classroom learning?” Commun. ACM, vol. 47, no. 5, pp. 75–79, 2004.
[3] J. Seely Brown, “Open education, the long tail, and learning 2.0,” Educause Rev., vol. 43, no. 1, pp. 16–20, 2008.
I. Uddin et al.: Systematic Mapping Review on MOOCS

[1] W. Ping, “The latest development and application of massive open online course: From cMOOC to xMOOC,” Mod. Distance Educ. Res., vol. 4, no. 2, pp. 54–67, Oct. 2017.

[2] J. D. Shah, “Year of MOOC-based degrees: A review of MOOC stats and trends in 2018,” Class Central, Online Blogpost, Tech. Rep., Mar. 2020. [Online]. Available: https://www.class-central.com/report/moocs-stats-and-trends-2018

[3] D. Shah, By the Numbers: MOOCS in 2015-Class Central’s MOOC Tech. Rep., 2010. Accessed: Jun. 2020. [Online]. Available: https://www.oerknowledgecloud.org/archive/MOOC_Final.pdf

[4] E. Scanlon, “Scholarship in the digital age: Open educational resources, publication and public engagement,” Brit. J. Educ. Technol., vol. 45, no. 1, pp. 12–23, Jan. 2014.

[5] S. Carson, “The unwalled garden: Growth of the open courseware consortium, 2001–2008,” Open Learn., J. Open, Distance E-Learn., vol. 24, no. 4, pp. 23–29, 2009.

[6] L. Pappano, “The Year of the MOOC,” The New York Times, vol. 2, no. 12, p. 2012, 2012.

[7] A. S. Sunar, N. A. Abdullah, S. White, and H. C. Davis, “Personalisation,” in Proc. 5th Int. Conf. Learn. Anal. Knowl., 2015, pp. 156–165.

[8] A. S. Sunar, N. A. Abdullah, S. White, and H. C. Davis, “Personalisation of MOOCs: The state of the art,” Inst. Repository. Univ. Southampton, Southampton, U.K., Tech. Rep., 2015. Accessed: Jul. 2020. [Online]. Available: https://eprints.soton.ac.uk/377471/1/syse_CSEDU_final.pdf

[9] E. Scanlon, “Scholarship in the digital age: Open educational resources, publication and public engagement,” Brit. J. Educ. Technol., vol. 45, no. 1, pp. 12–23, Jan. 2014.

[10] S. Bayne and J. Ross, “The pedagogy of the massive open online course,” Int. J. Speech Technol., vol. 24, no. 4, pp. 454–467, Oct. 2017.

[11] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, “Evaluating collaborative filtering recommender systems,” ACM Trans. Inf. Syst., vol. 22, no. 1, pp. 5–53, 2004.

[12] F. Dalipi, M. H. Goker, L. McGinty, and B. Smyth, “Case-based recommendation,” in Recommender Systems for Learning, Berlin, Germany: Springer, 2012.

[13] F. Dalipi, A. S. Imran, and Z. Kastrati, “MOOC dropout prediction using machine learning techniques: Review and research challenges,” in Proc. IEEE Global Eng. Educ. Conf. (EDUCON), Apr. 2018, pp. 1007–1014.

[14] A. Khalid, K. Lundqvist, and A. Yates, “Recommender systems for MOOCs based on neural networks,” in Recommender Systems for Learning, Berlin, Germany: Springer, 2012.

[15] D. Shah, “MOOC: Lessons learned from drop-out students,” in Proc. 1st ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[16] K. Mrhar, O. Douimi, and M. Abik, “A dropout predictor system in massive open online courses (MOOC),” in Proc. Int. Conf. Learn. Collaboration Technol. Cham, Switzerland: Springer, 2016, pp. 281–291.

[17] V. Gupta and S. R. Pandey, “Recommender systems for digital libraries: A review of concepts and concerns,” Library Philosophy Pract., pp. 1–9, Apr. 2019.

[18] D. Goldberg, D. Nichols, B. M. Oki, and D. Terry, “Using collaborative filtering to weave an information tapestry,” Commun. ACM, vol. 35, no. 12, pp. 61–70, 1992.

[19] S. Manouselis, H. Doukas, K. Vertebt, and E. Duval, Recommender Systems for Learning, Berlin, Germany: Springer, 2012.

[20] R. Mu, “A survey of recommender systems based on deep learning,” IEEE Access, vol. 8, pp. 69009–69022, 2020.

[21] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[22] I. Uddin, “Trends in 2018,” Class Central, Online Blogpost, Tech. Rep., Mar. 2020. [Online]. Available: https://www.class-central.com/report/moocs-stats-and-trends-2018

[23] F. Dalipi, A. S. Imran, and Z. Kastrati, “MOOC dropout prediction using machine learning techniques: Review and research challenges,” in Proc. IEEE Global Eng. Educ. Conf. (EDUCON), Apr. 2018, pp. 1007–1014.

[24] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[25] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[26] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[27] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[28] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[29] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[30] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[31] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[32] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[33] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[34] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.

[35] R. F. Kizilcec, M. Perez-Sanagustín, and J. J. Maldonado, “Recommending self-regulated learning strategies does not improve performance in a MOOC,” in Proc. 3rd ACM Conf. Learn. @ Scale, Apr. 2016, pp. 101–104.
[51] I. Portugal, P. Alencar, and D. Cowan, “The use of machine learning algorithms in recommender systems: A systematic review,” Expert Syst. Appl., vol. 97, pp. 205–227, May 2018.

[52] D. Gamage, S. Fernando, and I. Perera, “Quality of MOOCs: A review of literature on effectiveness and quality aspects,” in Proc. 8th Int. Conf. Ubiquitous Media Comput. (UMEDIA), Aug. 2015, pp. 224–229.

[53] D. L. Kusumastuti, A. N. Hidayanto, and H. Prabowo, “Models of adaptive learning system in MOOC: A systematic literature review,” in Proc. 9th Int. Conf. Inf. Educ. Technol. (ICICT), Mar. 2021, pp. 242–246.

[54] M. Saleemi, M. Anjum, and M. Rehman, “eServices classification, trends, and analysis: A systematic mapping study,” IEEE Access, vol. 5, pp. 26104–26123, 2017.

[55] S. B. Aher and L. M. R. J. Lobo, “Combination of machine learning algorithms for recommendation of courses in e-learning system based on historical data,” Knowl.-Based Syst., vol. 51, pp. 1–14, Oct. 2013.

[56] H. Fasihuddin, G. Skinner, and R. Athauda, “Towards an adaptive model to personalise open learning environments using learning styles,” in Proc. Int. Conf. Inf., Commun. Technol. Syst. (ICTS), Sep. 2014, pp. 183–188.

[57] V. R. Raghuvire, B. K. Tripathy, T. Singh, and S. Khanna, “Reinforcement learning approach towards effective content recommendation in MOOC environments,” in Proc. IEEE Int. Conf. MOOC. Innov. Technol. Educ. (MITE), Dec. 2014, pp. 285–289.

[58] R. G. Apaza, E. V. Cervantes, L. C. Quispe, and J. O. Luna, “Online courses recommendation based on LDA,” in Proc. SIMBIG, 2014, pp. 42–48.

[59] D. Yang, J. Shang, and C. P. Rosé, “Constrained question recommendation in MOOCs via submodularity,” in Proc. 23rd ACM Int. Conf. Conf. Knowl. Manage., Nov. 2014, pp. 1987–1990.

[60] D. Yang, M. Wen, and C. Rose, “Peer influence on attrition in massively open online courses,” in Educational Data Mining. London, U.K.: Educational Data Mining, 2014.

[61] D. Yang, M. Piergallini, I. Howley, and C. Rose, “Forum thread recommendation for massive open online courses,” in Educational Data Mining. London, U.K.: Educational Data Mining, 2014.

[62] D. Yanhui, W. Dequan, Z. Yongxin, and L. Lin, “A group recommender system for online course study,” in Proc. 7th Int. Conf. Inf. Technol. Med. Educ. (ITME), Nov. 2015, pp. 318–320.

[63] S.-W.-D. Li and P. Mitros, “Learnersourced recommendations for remediation,” in Proc. IEEE 15th Int. Conf. Adv. Learn. Technol., Jul. 2015, pp. 411–412.

[64] G. Sammour, A. Al-Zoubi, A. Gladun, K. Khalia, and J. Schreurs, “Semantic web and ontologies for personalisation of learning in MOOCs,” in Proc. 4th Int. Conf. Intell. Comput. Inf. Syst. (ICICIS), Dec. 2015, pp. 183–186.

[65] G. Venkataraman, C. Srinivasan, A. Ravichandran, S. Elias, and L. P. Ramesh, “Learning object recommendation for an effective open e-learning environment,” in Proc. IEEE Int. Conf. Sign. Process., Informat., Commun. Energy Syst. (SPICES), Feb. 2015, pp. 1–5.

[66] D. F. Fu, Q. Liu, S. Zhang, and J. Wang, “The undergraduate-oriented framework of MOOCs recommender system,” in Proc. Int. Symp. Educ. Technol. (ISET), Jul. 2015, pp. 115–119.

[67] V. Maran, J. P. M. D. Oliveira, P. Pietrobon, and I. Augustin, “Ontology network definition for motivational interviewing learning driven by semantic context-awareness,” in Proc. IEEE 28th Int. Symp. Comput.-Based Med. Syst., Jun. 2015, pp. 264–269.

[68] F. Bousbahri and H. Chorfi, “MOOC-rec: A case based recommender system for MOOCs,” Procedia-Social Behav. Sci., vol. 195, pp. 1813–1822, Jul. 2015.

[69] D. Onah and J. Sinclair, “Collaborative filtering recommendation method based on library classification ontology,” in Proc. Int. Conf. Logist., Informat. Service Sci. (LISS), Jul. 2016, pp. 1–5.

[70] Y. Dai, Y. Asano, and M. Yoshikawa, “Course content analysis: An initiative step toward learning object recommendation systems for MOOC learners,” in Proc. 9th Int. Conf. Educ. Data Mining (EDM), Jun. 2016, pp. 347–352.

[71] H. Song, “Research on network curriculum resources recommendation system based on MVC technology,” Revista Ibérica de Sistemas e Tecnologias de Informação, vol. 10, p. 62, Nov. 2016.

[72] J. J. Williams, L. Hoang, and L. Charlin, “Combining dynamic A/B experimentation and recommender systems in MOOCs,” in RecSys Posters. Germany: CEUR Workshop Proceedings, 2016.

[73] G. Piao and J. G. Breslin, “Analyzing MOOC entries of professionals on LinkedIn for user modeling and personalized MOOC recommendations,” in Proc. Conf. User Modeling Adaptation Personalization, Jul. 2016, pp. 291–292.

[74] H. Labarte, R. Bachelet, F. Bouchet, and K. Yacel, “Increasing MOOC completion rates through social interactions: A recommendation system,” in Proc. EMOOCs Conf. 4th Eur. MOOCs Stakeholders Summit, Feb. 2016, p. 471.

[75] D. Estrela, S. Batista, D. Martinho, and G. Marreiros, “A recommendation system for online courses,” in Proc. World Conf. Inf. Syst. Technol. Cham, Switzerland: Springer, 2017, pp. 195–204.

[76] G. Chen, D. Davis, M. Krause, C. Hauff, and G.-J. Houben, “Buying time: Enabling learners to become earners with a real-world paid task recommender system,” in Proc. 7th Int. Learn. Anal. Knowl. Conf., 2017, pp. 578–579.

[77] S. Tang and Z. A. Pardos, “Personalized behavior recommendation: A case study of applicability to 13 courses on edX,” in Proc. 25th Conf. User Modeling, Adaptation Personalization, 2017, pp. 165–170.

[78] Z. A. Pardos, S. Tang, D. Davis, and C. V. Le, “Enabling real-time adaptivity in MOOCs with a personalized next-step recommendation framework,” in Proc. 4th ACM Conf. Learn. @ Scale, Apr. 2017, pp. 23–32.

[79] P. Babinec and I. Srba, “Education-specific tag recommendation in CQA systems,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adaptation Personalization, Jul. 2017, pp. 281–286.

[80] F. Bouchet, H. Labarte, K. Yacef, and R. Bachelet, “Comparing peer recommendation strategies in a MOOC,” in Proc. Adjunct Publication 25th Conf. User Modeling, Adaptation Personalization, Jul. 2017, pp. 129–134.

[81] Y. Pang, Y. Jin, Y. Zhang, and T. Zha, “Collaborative filtering recommendation for MOOC application,” Comput. Appl. Eng. Educ., vol. 25, no. 1, pp. 120–128, Jan. 2017.

[82] M. Furukawa and K. Yamaji, “Adaptive recommendation of teaching materials based on free descriptions in MOOC course,” in Proc. 6th IIAI Int. Congr. Appl. Informat. (IIAA-AI), Jul. 2017, pp. 1011–1012.

[83] Y. Li and H. Li, “MOOC-FRS: A new fusion recommender system for MOOCs,” in Proc. IEEE 2nd Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC), Mar. 2017, pp. 1481–1488.

[84] X. He, P. Liu, and W. Zhang, “Design and implementation of a unified mooc recommendation system for social work major: Experiences and lessons,” in Proc. 7 IEEE Int. Conf. Comput. Sci. Eng. (CSE) IEEE Int. Conf. Embedded Ubiquitous Comput. (EUC), Jul. 2017, pp. 219–223.

[85] H. Hajian, Y. Bourda, and F. Popineau, “MORS: A system for recommending OERs in a MOOC,” in Proc. IEEE 17th Int. Conf. Adv. Learn. Technol. (ICALT), Jul. 2017, pp. 50–52.

[86] Y.-S. Su, T.-J. Ding, J.-H. Lue, C.-F. Lai, and C.-N. Su, “Applying big data analysis technique to students’ learning behavior and learning resource recommendation in a MOOCs course,” in Proc. Int. Conf. Appl. Syst. Innov. (ICASI), May 2017, pp. 1229–1230.

[87] B. Shapata, A. Kyselov, and G. Kyselov, “Exploring the vector space model for online courses,” in Proc. IEEE 1st Ukranie Conf. Electr. Comput. Eng. (UKRON), May 2017, pp. 861–864.

[88] H.-H. Wang, C. Chootong, A. Ochirbat, W. Sommool, W. K. T. M. Gunaratna, and K. T. Shih, “Online courses recommendation system based on industry occupation skills requirements,” in Proc. 10th Int. Conf. Ubiqu. Media Comput. Workshops (Ubimedia), Aug. 2017, pp. 1–6.
T.-Y. Yang, C. G. Brinton, and C. Joe-Wong, “Predicting learner knowledge-based approach for recommending massive learning activities,” in Proc. IEEE/ACS 14th Int. Conf. Comput. Syst. Appl. (AICCSA), Oct. 2017, pp. 49–54.

H. Zhang, H. Yang, T. Huang, and G. Zhan, “DBNCF: Personalized courses recommendation system based on DBN in MOOC environment,” in Proc. Int. Symp. Educ. Technol. (ISET), Jan. 2017, pp. 106–108.

E. A. Taha, E. K. Kamal Eddine, and C. Mohamed, “Toward a new framework of recommender memory based system for MOOCs,” Int. J. Electr. Comput. Eng. (IJECCE), vol. 7, no. 4, pp. 2152, Aug. 2017.

W. Intayoad, T. Becker, and P. Temdee, “Social context-aware recommendation for personalized online learning,” Wireless Pers. Commun., vol. 97, no. 1, pp. 163–179, Nov. 2017.

S. Prabhakar, G. Spanakis, and O. Zaiane, “Reciprocal recommender system for learners in massive open online courses (MOOCs),” in Proc. Int. Conf. Web-Based Learn. Cham, Switzerland: Springer, 2017, pp. 157–167.

H. C. Ouertani and M. M. Alawadh, “MOOCs recommender system: A recommender system for the massive open online courses,” in Innovations in Smart Learning. Singapore: Springer, 2017, pp. 139–143.

F. Mi and B. Faltings, “Adaptive sequential recommendation for discussion forums on MOOCs using context trees,” in Proc. 10th Int. Conf. Educ. Data Mining, 2017, p. 24.

Y. Wang, B. Liang, W. Ji, S. Wang, and Y. Chen, “Providing personalized learning guidance in MOOCs by multi-source data analysis,” World Wide Web, vol. 22, no. 3, pp. 1189–1219, May 2019.

Y. Pang, N. Wang, Y. Zhang, Y. Jin, W. Ji, and W. Tan, “Prerequisite-related MOOC recommendation on learning path locating,” Comput. Appl. Intell., vol. 26, no. 6, pp. 2071–2083, Nov. 2018.

H. Zhang, T. Huang, Z. Lv, S. Liu, and Z. Zhou, “MCRS: A course recommendation system for MOOCs,” Multimedia Tools Appl., vol. 77, no. 6, pp. 7051–7069, Mar. 2018.

Y. Pang, W. Liu, Y. Jin, H. Peng, T. Xia, and Y. Wu, “Adaptive recommendation for MOOC with collaborative filtering and time series,” Comput. Appl. Eng. Educ., vol. 26, no. 6, pp. 2071–2083, Nov. 2018.

Y. Pang, L. Li, W. Tan, Y. Jin, and Y. Zhang, “Forgetting punished recommendations for MOOCs,” in Proc. Int. Conf. Comput. Social Netw. Cham, Switzerland: Springer, 2018, pp. 415–426.

M. Cooper, J. Zhao, C. Bhatt, and D. A. Shamma, “MOOCes: Exploring educational video via recommendation,” in Proc. ACM Int. Conf. Multimedia Retal., 2018, pp. 521–524.

Y. Pang, C. Liao, W. Tan, Y. Wu, and C. Zhou, “Recommendation for MOOC with learner neighbors and learning series,” in Proc. Int. Conf. Web Intell. Inf. Syst. Eng. (WI-ISE), vol. 2, pp. 379–394, Oct. 2018.

X. Li, T. Wang, H. Wang, and J. Tang, “Understanding user interests acquisition in personalized online course recommendation,” in Proc. Asia–Pacific Web (APWeb) Web-Age Inf. Manage. (WAIM) Joint Int. Conf. Web Big Data. Cham, Switzerland: Springer, 2018, pp. 230–242.

K. Rabahallah, L. Mahdaoui, and F. Aouazou, “MOOCs recommender system using ontology and memory-based collaborative filtering,” in Proc. 20th Int. Conf. Enterprise Inf. Syst., 2018, pp. 635–641, Nov. 2018.

M. Harrathi, N. Touzani, and R. Braham, “Toward a personalized recommender system for learning activities in the context of MOOCs,” in Proc. Int. Conf. Intel. Interact. Multimedia Syst. Services. Cham, Switzerland: Springer, 2018, pp. 575–583.

S. Bouzayane and I. Saad, “Recommender system to improve knowledge sharing in massive open online courses,” in Proc. 10th Int. Joint Conf. Knowl. Discovery, Knowl. Eng. Knowl. Manage., 2018, pp. 51–60.

M. Zhang, J. Zhu, Z. Wang, and Y. Chen, “Providing personalized learning guidance in MOOCs by multi-source data analysis,” World Wide Web, vol. 22, no. 3, pp. 1189–1219, May 2019.

Y. Pang, N. Wang, Y. Zhang, Y. Jin, W. Ji, and W. Tan, “Prerequisite-related MOOC recommendation on learning path locating,” Comput. Appl. Intell., vol. 26, no. 6, pp. 2071–2083, Nov. 2018.

H. Zhang, T. Huang, Z. Lv, S. Liu, and H. Yang, “MOOCRC: A highly accurate resource recommendation model for use in MOOC environments,” Mobile Netw. Appl., vol. 24, no. 1, pp. 34–46, Feb. 2019.

M. Agrebi, M. Sendi, and M. Abed, “Deep reinforcement learning for personalized recommendation of distance learning,” in Proc. World Conf. Inf. Syst. Technol. Cham, Switzerland: Springer, 2019, pp. 597–606.

Z. Xiaoyuan and B. Jie, “Research on MOOC system based on bipartite graph context collaborative filtering algorithm,” in Proc. 8th Int. Conf. Softw. Comput. Appl., Feb. 2019, pp. 154–158.

W. Jiang and Z. A. Pardos, “Time slice imputation for personalized goal-based recommendation in higher education,” in Proc. 13th ACM Conf. Recomendator Syst., Sep. 2019, pp. 506–510.

D. Chao, L. Kaili, Z. Jing, and J. Xie, “Collaborative filtering recommendation algorithm classification and comparative study,” in Proc. 4th Int. Conf. Distance Educa. Learn., May 2019, pp. 106–111.

O. Vélez-Langs and I. Caececastro, “Recommender systems for an enhanced mobile e-learning,” in Proc. Int. Conf. Hum.-Comput. Interact. Cham, Switzerland: Springer, 2019, pp. 357–365.

H. Hajiri, Y. Bourda, and F. Popineau, “Personalized recommendation of open educational resources in MOOCs,” in Computer Supported Education (Communications in Computer and Information Science). Funchal, Portugal: Springer, 2019, pp. 166–190.

N. M. Ndyia, V. Chabbi, K. Lekdiou, and C. Lishou, “Recommending system for digital educational resources based on learning analysis,” in Proc. New Challenges Data Sci.: Acts 2nd Conf. Moroccan Classification Soc., Mar. 2019, pp. 1–6.

A. S. Lan, L. C. Spencer, Z. Chen, C. G. Brinton, and M. Chiang, “Personalized thread recommendation for MOOC discussion forums,” in Proc. Joint Eur. Conf. Mach. Learn. Knowl. Discovery Databases. Cham, Switzerland: Springer, 2018, pp. 725–740.

S. Assami, N. Daoudi, and R. Ajhoun, “Ontology-based modeling of a personalized MOOC recommender system,” in Proc. Int. Conf. Eur. Middle East North Africa Inf. Syst. Technol. Support Learn. Cham, Switzerland: Springer, 2018, pp. 21–28.

A. Chanaa and N.-E. El Faddouli, “Context-aware factorization mechanism for recommendation in massive open online courses(MOOCs),” in Proc. Int. Conf. Wireless Technol., Embedded Intell. Syst. (WAIM), Apr. 2019, pp. 1–6.

L. Singelmann, E. Swartz, M. Pearson, R. Striker, and E. A. Vazquez, “Design and development of a machine learning tool for an innovative MOOC platform,” in Proc. IEEE Learn. With MOOCs (LWMOOCs), Oct. 2019, pp. 105–109.

B. Faqghi, N. Daoudi, and R. Ajhoun, “Proposition of the recommendation system for the author based on similarity degrees,” in Proc. 1st Int. Conf. Smart Syst. Data Sci. (ICSSD), Oct. 2019, pp. 1–7.

S. Sakboonyarat and P. Tantatsanawong, “Massive open online courses (MOOCs) recommendation modeling using deep learning,” in Proc. 23rd Int. Conf. Comput. Sci. Eng. (ICSEC), Oct. 2019, pp. 275–280.
M. Zhang, S. Liu, and Y. Wang, “STR-SA: Session-based thread recommendation based on trust model for sustainable social tutoring in MOOCs,” in Proc. 1st Int. Conf. Smart Syst. Data Sci. (ICSSD), Oct. 2019, pp. 1–9.

B. D. Rahma and K. M. Koutheair, “Towards a framework for building automatic recommendations of answers in MOOCs’ discussion forums,” in Proc. 7th Int. Conf. ICT Acceptability (ICTA), Dec. 2019, pp. 1–6.

S. Assami, N. Daoudi, and R. Ajhoun, “Exploring social media data for MOOC recommendation,” in Proc. Int. Conf. Syst. Collaborat. Big Data, Internet Things Secur. (SysCoBiTS), Dec. 2019, pp. 1–8.

S. Aryal, A. S. Porawagama, M. G. S. Hasith, S. C. Thoradeniya, N. Kodagoda, and K. Suriyawansa, “MOOCRec: Learning styles-oriented MOOC recommender and search engine,” in Proc. IEEE Global Eng. Educ. Conf. (EDUCON), Apr. 2019, pp. 1167–1172.

S. Hilmy, T. De Silva, S. Pathirana, N. Kodagoda, and K. Suriyawansa, “MOOCs recommender based on user preference, learning styles and forum activity,” in Proc. Int. Conf. Advancements Comput. (ICAC), Dec. 2019, pp. 180–185.

S. R. Nangi, Y. Kanchugantla, P. G. Rayapati, and P. K. Bhowmik, “OfiViD: A system for linking off-topic concepts to topically relevant video lecture segments,” in Proc. IEEE 19th Int. Conf. Adv. Learn. Technol. (ICALT), Jul. 2019, pp. 37–41.

F. Fazuludeen, G. Vijayakumar, Z. A. Mahroof, N. Kodagoda, and K. Suriyawansa, “MOOCRec 2 for humanities-learning style based MOOC recommender and search engine,” in Proc. Int. Conf. Advance- ments Comput. (ICAC), Dec. 2019, pp. 470–475.

T. Xia, “An e-learning support middleware with MOOC course recommendation,” in Proc. 14th Int. Conf. Comput. Sci. Educ. (ICCSSE), Aug. 2019, pp. 596–600.

A. Tripathi, T. S. Ashwin, and R. M. R. Gudetti, “EmoWare: A context-aware framework for personalized video recommendation using affective video sequences,” IEEE Access, vol. 7, pp. 51185–51200, 2019.

Q. Lu and J. Xia, “Research on the application of item-based collabora- tive filtering algorithms in MOOC,” in Proc. J. Phys., Conf. 2019, vol. 1302, no. 3, Art. no. 032020.

H. Liu and X. Li, “Learning path combination recommendation based on grades,” in Proc. Int. Conf. Comput. Sci., Eng. Appl., Dec. 2020, pp. 1–5.

H. Sebbaq, N.-E. el Faddouli, and S. Bennani, “Recommender system based on trust model for sustainable social tutoring in MOOCs,” in Proc. 1st Int. Conf. Smart Syst. Data Sci. (ICSSD), Oct. 2019, pp. 1–9.

J. Gong, S. Wang, J. Wang, W. Feng, H. Peng, J. Tang, and P. S. Yu, “Graph neural networks for knowledge concept recommendation in MOOCs in a heterogeneous view,” in Proc. 43rd Int. ACM SIGIR Conf. Res. Develop. Inf. Retr., Jul. 2020, pp. 79–88.

W. Yao, H. Sun, and X. Hu, “A novel search ranking method for MOOCs using unstructured course information,” Wireless Commun. Mobile Comput., vol. 2020, Sep. 2020, Art. no. 8813615.

F. Fauzani, D. Nurjanah, and R. Rismala, “Apriori association rule for course recommender system,” Indonesian J. Comput. (Indo-JC), vol. 5, no. 1, pp. 16–20, 2020.

T. L. E. Vo, K. Nguyen, and B. Le, “Improving deep matrix factorization with normalized cross entropy loss function for graph-based MOOC recommendation,” in Proc. Int. Conf. Comput. Graph., Vis., Comput. Vis. Image Process. (CVGVIP), 2020, pp. 141–148. [Online]. Available: https://www.cgv-conf.org/.
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