IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 14, 2021, accepted June 23, 2021, date of publication July 29, 2021, date of current version September 1, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3101039

A Systematic Mapping Review on MOOC Recommender Systems

IMRAN UDDIN[1,2], ALI SHARIQ IMRAN[3], (Member, IEEE), KHAN MUHAMMAD[4], (Member, IEEE), NOSHEEN FAYYAZ[5], AND MUHAMMAD SAJJAD[1,3]

[1]Digital Image Processing Laboratory, Department of Computer Science, Islamia College University Peshawar, Peshawar 25000, Pakistan
[2]Institute of Computer Sciences and Information Technology (ICS/IT), The University of Agriculture Peshawar, Khyber Pakhtunkhwa 25000, Pakistan
[3]Color and Visual Computing Laboratory, Department of Computer Science (IDI), Norwegian University of Science and Technology (NTNU), 2815 Gjøvik, Norway
[4]Visual Analytics for Knowledge Laboratory (VIS2KNOW Lab), School of Convergence, College of Computing and Informatics, Sungkyunkwan University, Seoul 03063, Republic of Korea
[5]Department of Computer Science, University of Peshawar, Peshawar, Khyber Pakhtunkhwa 25000, Pakistan

Corresponding authors: Muhammad Sajjad (muhammad.sajjad@icp.edu.pk; muhammad.sajjad@ntnu.no) and Khan Muhammad (khan.muhammad@ieee.org)

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 Cormeir to outline George Siemens and Stephen Downes online course 'CCK08' [8]. MOOCs are further classified into two categories, cMOOC (Connectivist-Massive

The associate editor coordinating the review of this manuscript and approving it for publication was Pasquale De Meo.

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''[1] 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[2] in 2007-2008 and ''Personal Learning Environments, Networks and Knowledge'' offered by the Athabasca University[3] [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] 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 MOOCRS [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 Kusumastuti [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

[1] https://sites.google.com/site/themoocguide/3-cck08—the-distributed-course

[2] http://eci831.ca/about/

[3] https://tekri.athabascau.ca/content/personal-learning-environments-networks-and-knowledge

TABLE 1. Relevant surveys.

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 eLearning 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 the 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 MOOCRSbased 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. This survey also provides future research directions.

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.

TABLE 2. Research questions.

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 metrices 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.

TABLE 3. Mendeley search results.

Search Keyword	Relevant Studies
MOOC Recommender systems	36
MOOC Recommendation systems	41
MOOC recommendation	119
Total	**196**

Repositories used for re-searching the papers were IEEEXplore, 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**.

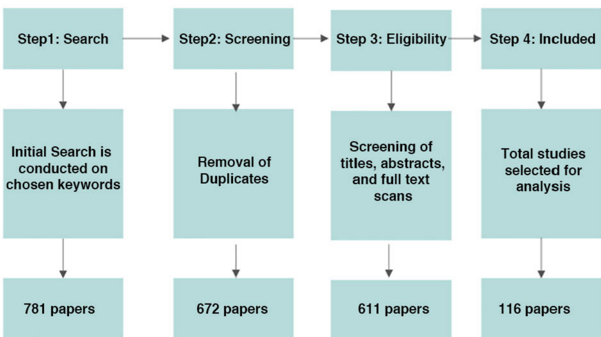


FIGURE 1. Identification process of primary studies.

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

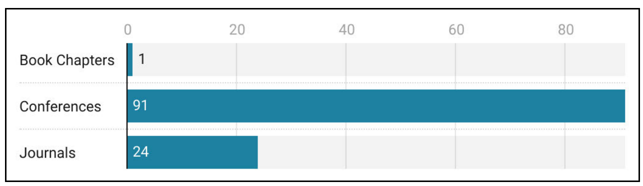


FIGURE 2. Distribution of selected literature (2013-2021).

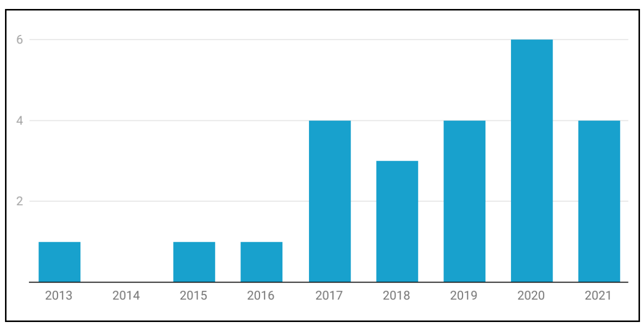


FIGURE 3. Studies published in Journals between 2013-2021.

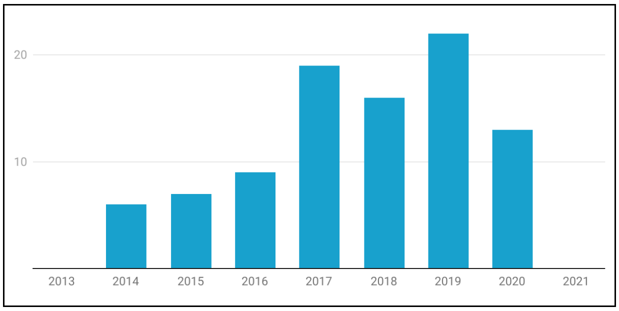


FIGURE 4. Studies published in Conferences between 2013-2021.

TABLE 6. Summary of the included literature.

Studies	Year	Type	Publisher
[55]	2013	Journal	Science Direct
[56, 57]	2014	Conference	IEEE
[58]	2014	Conference	SIMBig 2014
[59]	2014	Conference	ACM
[60, 61]	2014	Conference	EDM
[62-67]	2015	Conference	IEEE
[68]	2015	Journal	Elsevier
[69]	2015	Conference	INTED2015
[70]	2016	Conference	ICRTEST
[71-74]	2016	Conference	IEEE
[75]	2016	Conference	EDM
[76]	2016	Journal	RISTI
[77, 78]	2016	Conference	ACM
[79]	2016	Conference	EMOOCS
[80-85]	2017	Conference	ACM
[86]	2017	Journal	John Wiley & Sons
[87-96]	2017	Conference	IEEE
[97]	2017	Journal	IJECE
[98]	2017	Journal	Springer
[99]	2017	Conference	Springer
[100]	2017	Book Chapter	Springer
[101]	2017	Conference	EDM
[102]	2017	Journal	Emerald Publishing
[103-109]	2018	Conference	IEEE
[110-112]	2018	Conference	ACM
[113]	2018	Journal	Springer
[114]	2018	Journal	John Wiley & Sons
[115-118]	2018	Conference	Springer
[119]	2018	Conference	ICEIS
[120]	2018	Conference	Site press
[121]	2018	Conference	KOED
[122-124]	2019	Journal	Springer
[125-127]	2019	Conference	ACM
[128-133]	2019	Conference	Springer
[134-145]	2019	Conference	IEEE
[146]	2019	Journal	IEEE
[147]	2019	Journal	Institute of Physics Pub
[148]	2020	Journal	Springer
[149]	2020	Conference	Springer
[150]	2020	Journal	iJES
[151]	2020	Journal	jJET
[152-156]	2020	Conference	IEEE
[157]	2020	Journal	Institute of Physics Pub
[158-162]	2020	Conference	ACM
[163]	2020	Journal	Hindawi
[164]	2020	Journal	Indo-JC
[165]	2020	Conference	MCCSIS
[166]	2020	Conference	NIDL
[167]	2021	Journal	PLOS ONE
[168]	2021	Journal	Hindawi
[169]	2021	Journal	AJET
[170]	2021	Journal	IEEE

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 (IJECE)	IJECE	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)	iJES	1
Journal of Physics: Conference Series	IOPscience	2
Wireless Communication & Mobile Comping	Hindawi	1
Indonesia Journal of Computing (Indo-JC)	Indo-JC	1
International Journal of Emerging Technologies in Learning (iJET)	iJET	1
PLOS ONE	PLOS ONE	1
Complexity	Hindawi	1
Australasian Journal of Educational Technology (AJET)	AJET	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:

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?

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.[4]

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[5] or edX[6] 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

[4]https://github.com/pmitros/RecommenderXBlock

[5]https://www.coursera.org/

[6]https://www.edx.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: 6.00.1x-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 (5139) 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
[110]	StackSample: 10% of Stack Overflow Q&A [175]	https://www.kaggle.com/stackoverflow/stacksample
[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
[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]	Movielense 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.ec-lyon.fr/
[146]	FilmStim movie dataset	https://sites.uclouvain.be/ipsp/FilmStim/

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://datastage.stanford.edu/StanfordMoocPosts/	Require submitting request to Stanford University
[140]	Dataset of LinkedIn profiles of company employees	https://www.reddit.com/r/dataisbeautiful/comments/25qjpz/how_many_employees_are_moving_between_companies_oc/chjvd0g/
[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]	Muhammadia School of Engineers Forum	Closed
[152]	MOOC platform dataset of three courses offered by the Chinese Universities, including "Microeconomics", "Finance" and "Introduction to Programming ü 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]	XuetanдX MOOC platform	Closed
[163]	Coursera 2399 courses and 3981 course skills	EMAIL to wqyao@ustc.edu.cn for the data.
[164]	Canvas Network dataset from Harvard and MIT	https://dataverse.harvard.edu/dataverse/mxhx
[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

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 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. Rabahallah *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 Alawadh [100] for course recommendations. Furthermore, learning analytics were used in Chen *et al.* [81] using data from UpWork[7] to recommend relevant courses to the learner. Ontology based techniques in Sammour *et al.* [64] and Campos *et al.* [105] were used for course recommendations.

Machine learning was also found in the literature to recommend courses. Aher and Lobo [55], Li *et al.* [118] and Mondal *et al.* [155] used k-means and Apriori association algorithms. Similarly, Song [76] used machine factorization technique. Moreover, Su *et al.* [91] proposed a big data analytics technique. Wang *et al.* [93] used a clustering algorithm. Furthermore, Jain [108] used k-nearest neighbor, decision tree and CN2 rule induction, Zhang *et al.* [113] used Apriori algorithm with Spark model and Xia [145] used vector space mode (VSM) to achieve course recommendations. Yao *et al.* [163] and Fauzan [164] used K-mode to cluster and Apriori association rule for course recommendation.

[7] https://www.upwork.com

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 Hajri *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. Shaptala *et al.* [90] proposed a MOOC based OER system (MORS) which recommended OERs to the learners by modeling the MOOC and creating process to query OERs. Faqihi *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 Elghomary 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 Koutheair [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.

TABLE 11. Studies based on collaborative filtering techniques.

Ref.	Model	Recommender	Evaluation Matric
[60]	Matrix factorization	Social	Survival Curve
[65]	Bayesian Networks	Objectives	Not mentioned
[66]	Nearest Neighbor	Course	Cosine Similarity
[68]	Nearest Neighbor	Course	Levenshtein distance
[69]	Collaborative Framework in Python	Course	Not mentioned
[70]	Explicit Feedback	Course	MSE/results
[72]	Machine Learning to classify Learning Styles	Resource Recommender	Not mentioned
[86]	K-Nearest Neighbor (KNN), LSH and MinHash	Course	Precision/ Recall/ F-score
[89]	Item-based filtering and user-based filtering combined	Resource recommender	Accuracy/Recall
[99]	Similarity Matrix	Peer recommendation	Precision, Recall and F-Measure
[102]	Multivariate Weight Algorithm	Personalized Learning	Recall
[115]	Forgetting-Punished	Pre-requisite /subsequent objectives	Not mentioned
[123]	Learner location tracking inside MOOC	Pre-requisite /subsequent objectives	Not mentioned
[126]	Bipartite Graph Context	Personalized Learning	MAE/RMSE
[147]	Item Based Collaborative filtering	Learning Resources	Not mentioned
[153]	Vector Spatial Model	Resources	User Satisfaction

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/contents 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. Touimi *et al.* [151] used latent

TABLE 12. Studies based on content based techniques.

Ref.	Model	Recommender	Evaluation Matric
[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

dirichlet allocation (LDA) to recommend answers to the learner via a chatbot in discussion forums showing as number of concepts increase the performance of LDA declines. Finally, [170] used genetic algorithm (GA) and ant colony optimization (ACO) algorithms in a knowledge based recommender system to provide learner with personalized learning path using learner background and job information. **Table 13** shows the summary of the studies found based on knowledge-based filtering techniques in the literature.

TABLE 13. Studies based on knowledge based filtering.

Ref.	Model	Recommender	Evaluation Matric
[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

4) CONTEXT-SENSITIVE FILTERING

This type of recommendation takes contextual information such as location, time, social data into account [37]. Intayoad *et al.* [98] employed k-nearest neighbor KNN and decision trees to classify passed and failed students. The paper proposed implementation of social context, i.e., the interaction between the learners and LO's in the MOOC. Hou *et al.* [109] employed an online learning algorithm for course recommendations with big data support using contextual hierarchal tree algorithms. The study proposed dissimilarity amongst the courses to handle huge dataset and used average regret and average reward to evaluate their experiments. **Table 14** shows the summary of the studies found based on context-sensitive 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 describe 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. Raghuveer *et al.* [57] used the semantic structure of the courses and constructive reward based learning algorithm to recommend learning objectives.

TABLE 14. Studies based on context-sensitive filtering.

Ref.	Model	Recommender	Evaluation Matric
[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 skilled 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 recommended OERs to the learners by modeling the MOOC and created 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. Faqihi *et al.* [136] simulated the need for a producer who is searching for educational resources and then used Euclidian distance to measure similarities. Assami *et al.* [140] confers that a learner profile is limited if MOOC plaforms are used to gather information, insisting on gathering information from social professional networks to enrich learner information for efficeint 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] proposed 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.

6) LEARNING ANALYTICS

Learning analytics is an educational data mining measurement that uses data mining techniques to collect and

TABLE 15. Studies based on ontology-based filtering.

Ref.	Model	Recommender	Evaluation Matric
[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 r	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 UpWork[8] 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. Mothukuri *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,

[8]https://www.upwork.com/

TABLE 16. Studies based on learning analytics.

Ref.	Model	Recommender	Evaluation Matric
[56]	Learning Style analysis	Objective Recommendation	Not Mentioned
[63]	Learner Feedback Analysis	Resource (MOOC Resources)	Not Mentioned
[71]	Explicit Feedback Analysis	Adaptive Learning	Not Mentioned
[75]	Latent Dirichlet Allocation	Learning Objective	nDCC
[79]	Chat Widget	Contact	Not Mentioned
[81]	Learner Analysis	Course	Not Mentioned
[85]	Three Peer Recommendation Techniques compared	Peer Recommender	Chi Square test
[87]	Free Descriptor Analysis	Content /Adaptive	Not Mentioned
[94]	Capturing agent that analyzes learner's style	Personalized Learning	Not Mentioned
[117]	Recommendation based on Learner Neighbor and Learner Series (RLNLS)	Resource (MOOC Resources)	Precision / Recall / F-score
[120]	Bloom's Taxonomy	Personalized Learning	Not Mentioned
[122]	Multi-Grained-NKT and Historical-BKT	Personalized Learning	nDCG / Mean Average Precision
[130]	Felder and Silverman's Learning Styles Model	Open Resource Recommender	Precision / Recall
[131]	Learner's Learning Trace Analysis	Personalized Learning resources recommendation	Not Mentioned
[138]	Trust Management System (TRS)	Peer Recommender	Not Mentioned
[148]	Learning Path combination recommendation method based on learning network (LPCRLN)	Learning Path Recommendation	Precision

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],

TABLE 17. Studies based on machine learning.

Ref.	Model	Recommender	Evaluation Matric Used
[55]	K-means/Association rule mining	Course Recommender	Support
[73]	Watch time log	Resource (Video)	Not mentioned
[76]	Machine Factorization	Course	Not mentioned
[77]	Thomas Sampling	Email	Regret
[84]	Support Vector Machines (SVM) and Random Forest (RF)	Tag recommendation	Precision, recall, F-Score
[91]	Big Data Analytics	Course	Not mentioned
[92]	Vector Space Modeling	Learning Resource	Cosine Distance
[93]	Clustering algorithm	Course	Jacquard's Similarity
[101]	Context Tree	MOOC Forum	Success rate
[106]	Clustering with K-means and hierarchical clustering	Resource Recommender	Average Silhouette Score
[108]	Random Forest, Classification Tree, K-Nearest Neighbors, Cn2 Rule and Logistics Regression	Course	Area under the (AUC) curve/ Average Accuracy /Precision/ recall/ F-score
[110]	LDA	MOOC	Precision/recall
[111]	Text Rank Algorithm	Content/Topic	Dissimilarity
[112]	TF-IDF	Content/Topic	Topic Redundancy/ Course Diversity
[113]	improved Apriori algorithm	Course	Support / Confidence
[118]	K-Means Clustering	Personalized Course	RMSE
[121]	Dominance-Based Rough set Approach (DBRSA)	Leader	F-measure, accuracy
[134]	Context aware Factorization Machine algorithm	Personalized Learning resources	Not mentioned
[132]	Point Process	Thread	Mean Average Precision
[139]	Random Forest	Forum Answer	F1-Score/ Accuracy
[143]	Concept Similarity Network and NLP techniques	Learning Resource Recommender (Off-Topic recommender)	
[145]	Vector Space Model (VSM)	Course	Precision/ recall/ F-score
[152]	Self-Attention mechanism	Thread	NDCG/ Recall
[155]	Data mining techniques	Course	RMSE / MAE
[163]	LDA with Course Ranking Algorithm	Course Recommender	Coherence Score
[164]	Apriori association rule algorithm, k-modes clustering	Course Recommender	Support / Confidence
[167]	Voting with Hyperspheres	Course Recommender	RMSE, Precision, Recall, F-score

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 Matric
[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

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 page, and Cooper *et al.* [116] employed LSTM to recommend videos.

TABLE 19. Studies based on hybrid approach.

Ref.	Model	Recommendation	Evaluation Matric
[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

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)

TABLE 20. Classification of studies based on techniques.

Technique	Studies
Collaborative filtering	[60, 65, 66, 68-70, 72, 86, 89, 99, 102, 115, 123, 126, 147, 153]
Content-based filtering	[61, 104, 159]
Knowledge Based filtering	[100, 151, 170]
Context Sensitive filtering	[98, 151, 170]
Ontology based filtering	[57, 64, 67, 74, 78, 90, 95, 105, 107, 133, 136, 140, 150, 160, 166, 169]
Learning analytics	[56, 63, 71, 75, 79, 81, 85, 87, 94, 117, 120, 122, 130, 131, 138, 148]
Machine learning	[55, 73, 76, 77, 84, 91-93, 101, 106, 108, 110-113, 118, 121, 132, 134, 139, 143, 145, 152, 155, 163, 164, 167]
Deep learning	[59, 82, 83, 96, 103, 116, 124, 125, 127, 137, 146, 154, 157, 162, 165]
Hybrid Approach	[58, 62, 80, 88, 97, 114, 119, 128, 129, 135, 141, 142, 144, 149, 156, 158, 161, 168]

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. Furthermore, logistic regression, k-nearest neighbor and support vector machines were used by Singelmann *et al.* [135] to recommended learning objectives. 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 matric 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

TABLE 21. Evaluation metric used in different studies.

Matric	Studies
Accuracy	[57, 82, 83, 89, 96, 110, 114, 119, 121, 123, 126, 133, 137, 139, 145, 156, 157, 168]
Area Under Accuracy (AUC)	[108]
Average Silhouette Score	[106]
Bounce Rate	[146]
Chi-square test	[85]
Course Diversity	[112]
Cosine Similarity	[92, 104, 111, 143, 158]
Course Completion Rates	[79]
Coherence Score	[159, 163]
Discounted Cumulative Gain (DCG)	[91]
Dissimilarity	[111]
Error	[141]
Hit Ratio	[154]
HCI Evaluation Technique(s)	[142]
Jacquard's Similarity	[93]
Lift Ratio	[164]
Loss	[156]
Mean Relative Error (MRE)	[114, 122]
Mean Absolute Error (MAE)	[114, 122, 128, 130, 155, 168]
Mean Average Precision	[61, 122, 132, 134, 138, 154]
Mean Square Error (MSE)	[71]
Mean Reciprocal Ranking	[78, 158]
Miss or Hit	[146, 162]
Normal Discounted Cumulative Gain (NDCG)	[75, 76, 91, 128, 153, 162, 165] [122] [152, 154]
Normalized Entropy	[83]
Objective Function Comparison	[59]
Objective values	[170]
Precision, Recall and F-Measure	[81, 89, 91, 96, 99, 105, 108, 113, 114, 116, 121, 122, 125, 127, 130, 136, 137, 139, 148, 150, 152, 153, 167]
Performance Cost Score (PCS)	[118]
Root Mean Square (RMSE)	[118, 124, 126, 128-130, 136, 155, 167, 168]
ROC Curve	[110]
Regret Rate	[77]
Regret Comparison	[109]
Reward Comparison	[57, 109]
Rating	[169]
Support and Confidence	[55, 98, 103, 113]
Survival Curve	[60]
Similarity Measurement	[74, 78, 119, 136, 151]
Success Rate	[78, 101]
SUS Score[196]	[169]
Time Accuracy (TAC)	[110]
Topic Redundancy	[112]
UPON methodology [197]	[67]
User Satisfaction	[153]

and ontology-based approaches to create intelligent hybrid recommender systems for MOOC.

D. RQ4. WHAT WERE THE EVALUATION METRICES 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
Columbia	[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
Netherland	[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, Netherland, 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
Netherland	[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

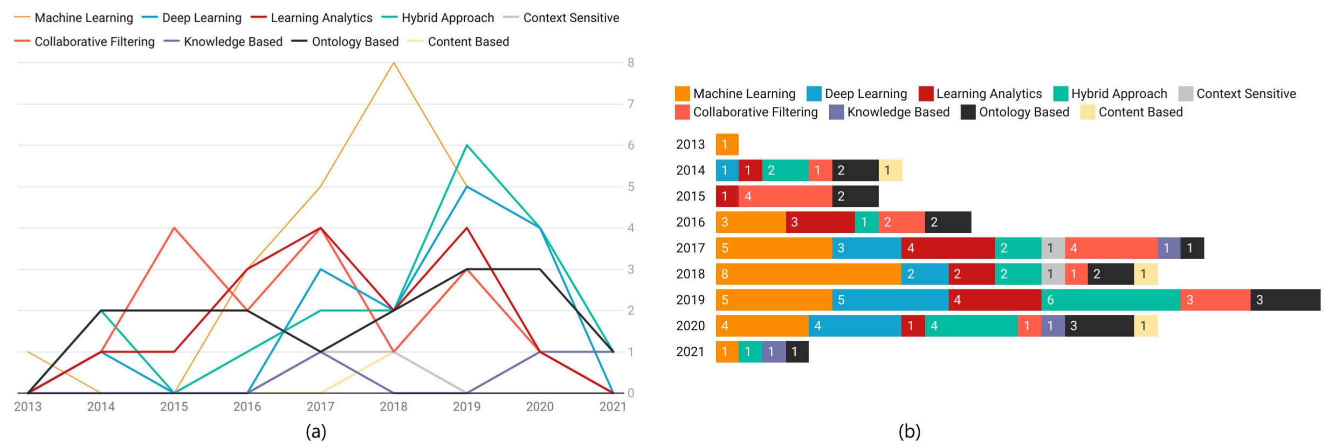


FIGURE 5. Trends of different technologies used in MOOCRS research. (a) MOOCRS Technologies and Trends (b) Frequency of technologies used in MOOCRS over the years.

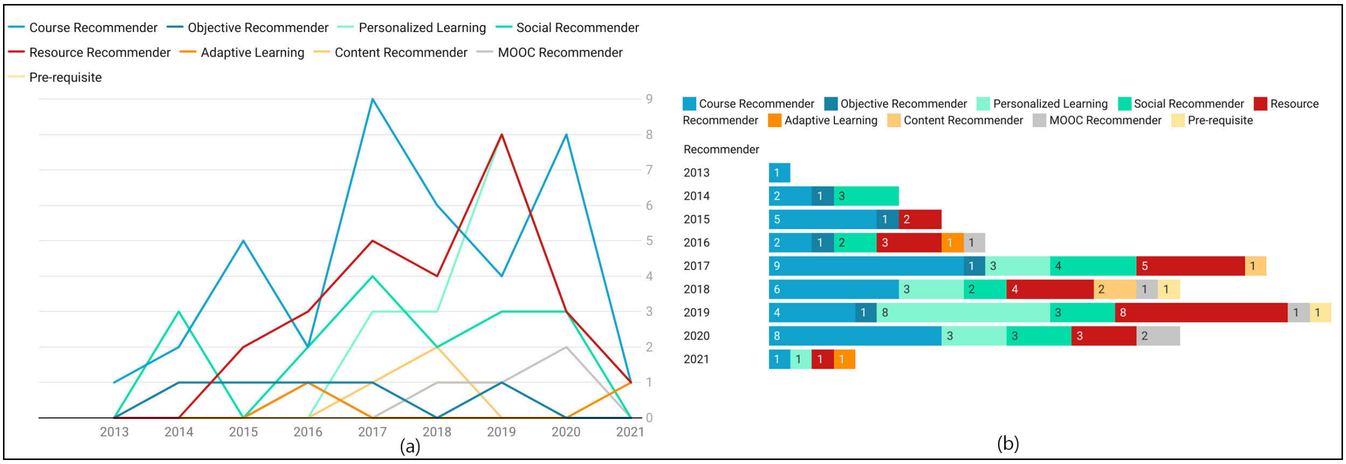


FIGURE 6. Trends in Different type of Recommenders. (a) Recommendation trends in studies. (b) Frequency of research on different MOOCRS.

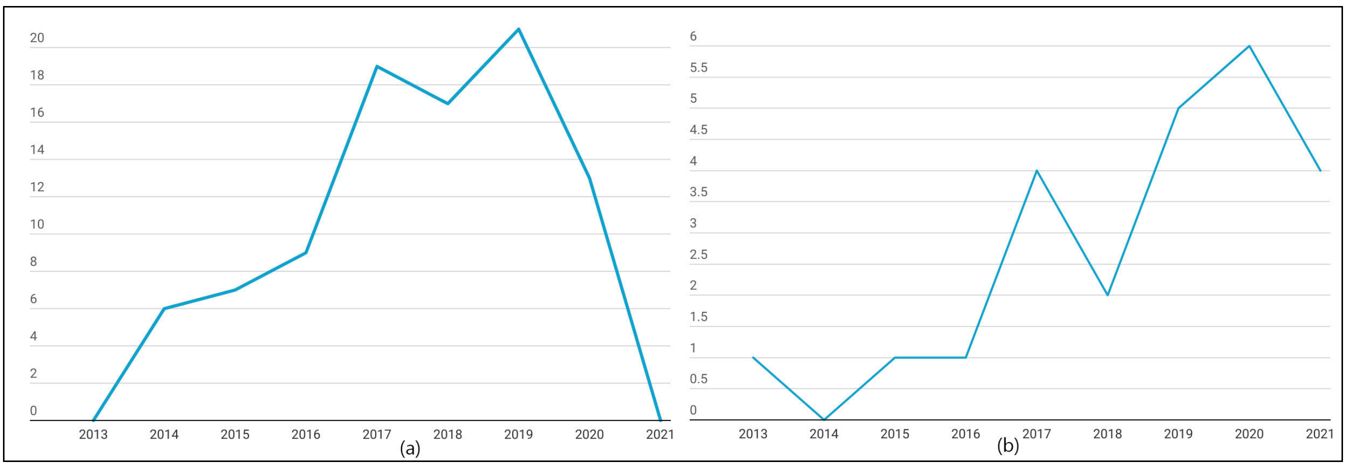


FIGURE 7. Trends of MOOCRS related publication. (a) Trend of MOOCRS in Journals. (b) Trend of MOOCRS research in Conferences.

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-104-2622-8-009-001 and MOST-104-3115- E-194-001"
[89]	China	"Financial 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. 2015LY81), 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/IP, 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. 2015BAK07B03), 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 Zoomi Inc."
[105]	Brazil	"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 2015BAK07B03), 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/RC/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"
[115]	China	"Funded by computer science and Technology subject of Shanghai Polytechnic University with No. xxkzd1604"
[118]	China	"Supported by the National Key Research and Development Program of China (2018YFB1004502), the National Natural Science Foundation of China (61702532) and the Key Program of National Natural Science Foundation of China (61532001, 61432020)"
[114]	China	"Funded by the Subject of Computer Science and Technology of Shanghai Polytechnic University with No. xxkzd1604 and financial No. B50NH17HZ01-41"
[122]	China	"Partially supported by the National Natural Science Foundation of China (NSFC Grant Nos.61472006, 61772039, and 91646202)"
[128]	China	"Financially supported by Ministry of Education of the People's Republic of China (Grant No.17YJA880030)"
[137]	Thailand	"Supported by Mahidol Witthayanusorn School, Thailand"
[145]	China	"Financially supported by the Key Disciplines o Shanghai Polytechnic University under Grant No. XXKZD1604"
[123]	China	"Funded by computer science and technology subject of Shanghai Poly-technic University with No. xxkzd1604"
[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]	China	"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 NSFC 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 III-1526499, III-1763325, III-1909323, CNS-1930941, 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

TABLE 24. ***(Continued.)*** **Studies and their funding/supporting agencies.**

		2018YFC0830804"
[169]	Spain	The FEDER/Ministerio de Ciencia, Innovación y Universidades Agencia Estatal de Investigación, through the Smartlet Project under Grant TIN2017-85179-C3-1-R, and in part by the Madrid Regional Government through the e-Madrid-CM Project under Grant S2018/TCS 4307, a project which is co-funded by the European Structural Funds (FSE and FEDER). Partial support has also been received from the European Commission through Erasmus+ Capacity Building in the Field of Higher Education projects, more specifically through projects LALA, InnovaT and PROF-XXI (586120-EPP-1-2017-1-ES-EPPKA2-CBHE-JP),(598758-EPP-1-2018-1-AT-EPPKA2-CBHE-JP), (609767-EPP 1-2019-1-ES-EPPKA2-CBHE-JP). This work has also been supported by the Madrid Government (Comunidad de Madrid-Spain) under the Multiannual Agreement with UC3M in the line of Excellence of University Professors (EPUC3M21), and in the context of the V PRICIT (Regional Programme of Research and Technological Innovation).

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.

[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 opencourseware consortium, 2001–2008," *Open Learn., J. Open, Distance e-Learn.*, vol. 24, no. 1, 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. Regalado, "The most important education technology in 200 years," *Technol. Rev.*, vol. 116, no. 1, pp. 61–62, 2013.

[8] A. McAuley, B. Stewart, G. Siemens, and D. Cormier, "The MOOC model for digital practice," Social Sci. Humanities Res. Council, Univ. Prince Edward Island, Charlottetown, PE, Canada, Tech. Rep., 2010. Accessed: Jun. 2020. [Online]. Available: https://www.oerknowledgecloud.org/archive/MOOC_Final.pdf

[9] W. Ping, "The latest development and application of massive open online course: From cMOOC to xMOOC," *Mod. Distance Educ. Res.*, vol. 3, no. 5, pp. 13–19, 2013.

[10] S. Joksimović, V. Kovanović, J. Jovanović, A. Zouaq, D. Gašević, and M. Hatala, "What do cMOOC participants talk about in social media?: A topic analysis of discourse in a cMOOC," in *Proc. 5th Int. Conf. Learn. Anal. Knowl.*, 2015, pp. 156–165.

[11] 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/377474/1/ayse_CSEDU_final.pdf

[12] D. Dumitrica, "Fixing higher education through technology: Canadian media coverage of massive open online courses," *Learn., Media Technol.*, vol. 42, no. 4, pp. 454–467, Oct. 2017.

[13] E. E. Blog. (2020). *xMOOC vs cMOOC? Defining Common MOOC Terms*. Accessed: Oct. 25, 2020. [Online]. Available: https://blog.extensionengine.com/xmooc-vs-cmooc#:~:text=xMOOC%20stands%20for%20eXtended%20Massive,exposed%20to%20university%2Dlevel%20courses

[14] S. Bayne and J. Ross, "The pedagogy of the massive open online course (MOOC): The UK view," Higher Educ. Acad. Ser. Ed., Heslington, U.K., Tech. Rep. 30, 2014.

[15] A. Khalid, K. Lundqvist, and A. Yates, "Recommender systems for MOOCs: A systematic literature survey (January 1, 2012–July 12, 2019)," *Int. Rev. Res. Open Distrib. Learn.*, vol. 21, no. 4, pp. 255–291, 2020.

[16] 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/

[17] J. Knox, "Beyond the 'c' and the 'x': Learning with algorithms in massive open online courses (MOOCs)," *Int. Rev. Educ.*, vol. 64, no. 2, pp. 161–178, 2018.

[18] D. Shah, *By the Numbers: MOOCS in 2015-Class Central's MOOC Report*, ed. Class Centeral Blogpost, 2015. [Online]. Available: https://www.classcentral.com/

[19] K. Mrhar, O. Douimi, and M. Abik, "A dropout predictor system in MOOCs based on neural networks," *J. Autom., Mobile Robot. Intell. Syst.*, vol. 14, pp. 72–80, Mar. 2021.

[20] K. Jordan, "Initial trends in enrolment and completion of massive open online courses," *Int. Rev. Res. Open Distrib. Learn.*, vol. 15, no. 1, pp. 133–160, Jan. 2014.

[21] D. F. Onah, J. Sinclair, and R. Boyatt, "Dropout rates of massive open online courses: Behavioural patterns," *Proc. EDULEARN*, vol. 1, 2014, pp. 5825–5834.

[22] C. Gütl, R. H. Rizzardini, V. Chang, and M. Morales, "Attrition in MOOC: Lessons learned from drop-out students," in *Proc. Int. Workshop Learn. Technol. Educ. Cloud.* Cham, Switzerland: Springer, 2014, pp. 37–48.

[23] R. F. Kizilcec, C. Piech, and E. Schneider, "Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses," in *Proc. 3rd Int. Conf. Learn. Anal. Knowl.*, 2013, pp. 170–179.

[24] D. Yang, T. Sinha, D. Adamson, and C. P. Rosé, "Turn on, tune in, drop out: Anticipating student dropouts in massive open online courses," in *Proc. NIPS Data-Driven Educ. Workshop*, vol. 11, 2013, p. 14.

[25] V. Sabnis, P. D. Tejaswini, and G. S. Sharvani, "Course recommendations in Moocs: Techniques and evaluation," in *Proc. 3rd Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solutions (CSITSS)*, Dec. 2018, pp. 59–66.

[26] 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.

[27] F. Dalipi, S. Y. Yayilgan, A. S. Imran, and Z. Kastrati, "Towards understanding the MOOC trend: Pedagogical challenges and business opportunities," in *Proc. Int. Conf. Learn. Collaboration Technol.* Cham, Switzerland: Springer, 2016, pp. 281–291.

[28] R. F. Kizilcec, M. Pérez-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] L. B. Marinho, A. Hotho, R. Jäschke, and A. Nanopoulos, *Recommender Systems for Social Tagging Systems*. Hildesheim, Germany: Univ. Hildesheim, 2009.

[30] A. Klašnja-Milićević, M. Ivanović, B. Vesin, and Z. Budimac, "Enhancing e-learning systems with personalized recommendation based on collaborative tagging techniques," *Int. J. Speech Technol.*, vol. 48, no. 6, pp. 1519–1535, Jun. 2018.

[31] 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.

[32] B. Kitchenham, O. P. Brereton, D. Budgen, M. Turner, J. Bailey, and S. Linkman, "Systematic literature reviews in software engineering-a systematic literature review," *Inf. Softw. Technol.*, vol. 51, no. 1, pp. 7–15, Jan. 2009.

[33] P. Resnick and H. R. Varian, "Recommender systems," *Commun. ACM*, vol. 40, no. 3, pp. 56–58, 1997.

[34] 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.

[35] 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.

[36] N. Manouselis, H. Drachsler, K. Verbert, and E. Duval, *Recommender Systems for Learning*. Berlin, Germany: Springer, 2012.

[37] C. C. Aggarwal, *Recommender Systems*. Cham, Switzerland: Springer, 2016.

[38] A. Felfernig and R. Burke, "Constraint-based recommender systems: Technologies and research issues," in *Proc. 10th Int. Conf. Electron. Commerce*, 2008, pp. 1–10.

[39] A. Felfernig, G. Friedrich, D. Jannach, and M. Zanker, "Developing constraint-based recommenders," in *Recommender Systems Handbook*. Boston, MA, USA: Springer, 2011, pp. 187–215.

[40] D. Bridge, M. H. Göker, L. McGinty, and B. Smyth, "Case-based recommender systems," *Knowl. Eng. Rev.*, vol. 20, no. 3, p. 315, 2005.

[41] R. Burke, "Knowledge-based recommender systems," *Encyclopedia Library Inf. Syst.*, vol. 69, no. 32, pp. 175–186, 2000.

[42] D. Lee, S. E. Park, M. Kahng, S. Lee, and S.-G. Lee, "Exploiting contextual information from event logs for personalized recommendation," in *Computer and Information Science*. Berlin, Germany: Springer, 2010, pp. 121–139.

[43] B. Smyth, "Case-based recommendation," in *The Adaptive Web*. Berlin, Germany: Springer, 2007, pp. 342–376.

[44] L. Lü, M. Medo, C. H. Yeung, Y.-C. Zhang, Z.-K. Zhang, and T. Zhou, "Recommender systems," *Phys. Rep.*, vol. 519, no. 1, pp. 1–49, 2012.

[45] D. B. Guruge, R. Kadel, and S. J. Halder, "The state of the art in methodologies of course recommender systems—A review of recent research," *Data*, vol. 6, no. 2, p. 18, 2021.

[46] E. Ashraf, S. Manickam, and S. Karuppayah, "A comprehensive review of course recommender systems in e-learning," *J. Educators Online*, vol. 18, no. 1, pp. 23–35, 2021.

[47] P. V. Kulkarni, S. Rai, and R. Kale, "Recommender system in elearning: A survey," in *Proc. Int. Conf. Comput. Sci. Appl.* Singapore: Springer, 2020, pp. 119–126.

[48] S. S. Khanal, P. Prasad, A. Alsadoon, and A. Maag, "A systematic review: Machine learning based recommendation systems for e-learning," *Educ. Inf. Technol.*, vol. 25, pp. 2635–2664, Dec. 2019.

[49] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Comput. Surv.*, vol. 52, no. 1, pp. 1–38, 2019.

[50] R. Mu, "A survey of recommender systems based on deep learning," *IEEE Access*, vol. 6, pp. 69009–69022, 2018.

[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. Ubi-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. (ICIET)*, 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. Raghuveer, 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. Inf. 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. Khala, and J. Schreurs, "Semantic web and ontologies for personalisation of learning in MOOCs," in *Proc. IEEE 7th 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. Signal Process., Informat., Commun. Energy Syst. (SPICES)*, Feb. 2015, pp. 1–5.
[66] D. 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, R. 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. Bousbahi 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 system: A framework in massive open online courses," in *Proc. INTED*, 2015, pp. 1249–1257.
[70] V. Garg and R. Tiwari, "Hybrid massive open online course (MOOC) recommendation system using machine learning," in *Proc. Int. Conf. Recent Trends Eng., Sci. Technol. (ICRTEST)*, Oct. 2016.
[71] A. Alzaghoul and E. Tovar, "A proposed framework for an adaptive learning of massive open online courses (MOOCs)," in *Proc. 13th Int. Conf. Remote Eng. Virtual Instrum. (REV)*, Feb. 2016, pp. 127–132.
[72] B. Hmedna, A. El Mezouary, O. Baz, and D. Mammass, "A machine learning approach to identify and track learning styles in MOOCs," in *Proc. 5th Int. Conf. Multimedia Comput. Syst. (ICMCS)*, Sep. 2016, pp. 212–216.
[73] H.-M. Chang, T. M.-L. Kuo, S.-C. Chen, C.-A. Li, Y.-W. Huang, Y.-C. Cheng, H.-H. Hsu, N.-F. Huang, and J.-W. Tzeng, "Developing a data-driven learning interest recommendation system to promoting self-paced learning on MOOCs," in *Proc. IEEE 16th Int. Conf. Adv. Learn. Technol. (ICALT)*, Jul. 2016, pp. 23–25.
[74] Y. Huang, "A course-oriented book recommendation method based on library classification ontology," in *Proc. Int. Conf. Logistics, Informat. Service Sci. (LISS)*, Jul. 2016, pp. 1–5.
[75] 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.
[76] 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.
[77] 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.
[78] 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.
[79] H. Labarthe, R. Bachelet, F. Bouchet, and K. Yacef, "Increasing MOOC completion rates through social interactions: A recommendation system," in *Proc. EMOOCS Conf. 4th Eur. MOOCS Stakeholders Summit*, Feb. 2016, p. 471.
[80] 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.
[81] 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.
[82] 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.
[83] 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.
[84] 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.
[85] F. Bouchet, H. Labarthe, 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.
[86] Y. Pang, Y. Jin, Y. Zhang, and T. Zhu, "Collaborative filtering recommendation for MOOC application," *Comput. Appl. Eng. Educ.*, vol. 25, no. 1, pp. 120–128, Jan. 2017.
[87] M. Furukawa and K. Yamaji, "Adaptive recommendation of teaching materials based on free descriptions in MOOC course," in *Proc. 6th IIAI Int. Congr. Adv. Appl. Informat. (IIAI-AAI)*, Jul. 2017, pp. 1011–1012.
[88] 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.
[89] 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.
[90] H. Hajri, 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.
[91] 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.
[92] R. Shaptala, A. Kyselova, and G. Kyselov, "Exploring the vector space model for online courses," in *Proc. IEEE 1st Ukraine Conf. Electr. Comput. Eng. (UKRCON)*, May 2017, pp. 861–864.
[93] H.-H. Wang, C. Chootong, A. Ochirbat, W. Sommool, W. K. T. M. Gunarathn, and T. K. Shih, "Online courses recommendation system based on industry occupation skills requirements," in *Proc. 10th Int. Conf. Ubi-Media Comput. Workshops (Ubi-Media)*, Aug. 2017, pp. 1–6.

[94] U. K. Mothukuri, B. V. Reddy, P. N. Reddy, S. Gutti, K. Mandula, R. Parupalli, C. H. A. S. Murty, and E. Magesh, "Improvisation of learning experience using learning analytics in eLearning," in *Proc. 5th Nat. Conf. E-Learning E-Learning Technol. (ELELTECH)*, Aug. 2017, pp. 1–6.

[95] M. Harrathi, N. Touzani, and R. Braham, "A hybrid knowlegde-based approach for recommending massive learning activities," in *Proc. IEEE/ACS 14th Int. Conf. Comput. Syst. Appl. (AICCSA)*, Oct. 2017, pp. 49–54.

[96] 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)*, Jun. 2017, pp. 106–108.

[97] 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. (IJECE)*, vol. 7, no. 4, p. 2152, Aug. 2017.

[98] 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.

[99] 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.

[100] 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.

[101] 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.

[102] Y. Wang, B. Liang, W. Ji, S. Wang, and Y. Chen, "An improved algorithm for personalized recommendation on MOOCs," *Int. J. Crowd Sci.*, vol. 1, no. 3, pp. 186–196, Sep. 2017.

[103] T.-Y. Yang, C. G. Brinton, and C. Joe-Wong, "Predicting learner interactions in social learning networks," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, Apr. 2018, pp. 1322–1330.

[104] R. Huang and R. Lu, "Research on content-based MOOC recommender model," in *Proc. 5th Int. Conf. Syst. Informat. (ICSAI)*, Nov. 2018, pp. 676–681.

[105] R. Campos, R. Pereira dos Santos, and J. Oliveira, "Web-based recommendation system architecture for knowledge reuse in MOOCs ecosystems," in *Proc. IEEE Int. Conf. Inf. Reuse Integr. (IRI)*, Jul. 2018, pp. 193–200.

[106] J. Chakraborty, G. Thopugunta, and S. Bansal, "Data extraction and integration for scholar recommendation system," in *Proc. IEEE 12th Int. Conf. Semantic Comput. (ICSC)*, Jan. 2018, pp. 397–402.

[107] S. Assami, N. Daoudi, and R. Ajhoun, "Personalization criteria for enhancing learner engagement in MOOC platforms," in *Proc. IEEE Global Eng. Educ. Conf. (EDUCON)*, Apr. 2018, pp. 1265–1272.

[108] H. Jain and Anika, "Applying data mining techniques for generating MOOCs recommendations on the basis of learners online activity," in *Proc. IEEE 6th Int. Conf. MOOCs, Innov. Technol. Educ. (MITE)*, Nov. 2018, pp. 6–13.

[109] Y. Hou, P. Zhou, J. Xu, and D. O. Wu, "Course recommendation of MOOC with big data support: A contextual online learning approach," in *Proc. IEEE INFOCOM-IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, Apr. 2018, pp. 106–111.

[110] T. Zarra, R. Chiheb, R. Faizi, and A. El Afia, "MOOCs' recommendation based on forum latent Dirichlet allocation," in *Proc. 2nd Int. Conf. Smart Digit. Environ.*, 2018, pp. 88–93.

[111] S. Ji, Y. Kim, S. Jung, and E. Hwang, "An educational video scoring scheme for level and topic-based recommendation," in *Proc. 12th Int. Conf. Ubiquitous Inf. Manage. Commun.*, Jan. 2018, pp. 1–5.

[112] J. Zhao, C. Bhatt, M. Cooper, and D. A. Shamma, "Flexible learning with semantic visual exploration and sequence-based recommendation of MOOC videos," in *Proc. CHI Conf. Hum. Factors Comput. Syst.*, Apr. 2018, pp. 1–13.

[113] 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.

[114] 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.

[115] Y. Pang, L. Li, W. Tan, Y. Jin, and Y. Zhang, "Forgetting punished recommendations for MOOC," in *Proc. Int. Conf. Comput. Social Netw.* Cham, Switzerland: Springer, 2018, pp. 415–426.

[116] M. Cooper, J. Zhao, C. Bhatt, and D. A. Shamma, "MOOCex: Exploring educational video via recommendation," in *Proc. ACM Int. Conf. Multimedia Retr.*, 2018, pp. 521–524.

[117] 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 Inf. Syst. Eng.* Cham, Switzerland: Springer, 2018, pp. 379–394.

[118] 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.

[119] K. Rabahallah, L. Mahdaoui, and F. Azouaou, "MOOCs recommender system using ontology and memory-based collaborative filtering," in *Proc. 20th Int. Conf. Enterprise Inf. Syst.*, 2018, pp. 635–641.

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

[121] 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.

[122] 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.

[123] Y. Pang, N. Wang, Y. Zhang, Y. Jin, W. Ji, and W. Tan, "Prerequisite-related MOOC recommendation on learning path locating," *Comput. Social Netw.*, vol. 6, no. 1, p. 7, Dec. 2019.

[124] 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.

[125] 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.

[126] Z. Xiaoyan 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.

[127] W. Jiang and Z. A. Pardos, "Time slice imputation for personalized goal-based recommendation in higher education," in *Proc. 13th ACM Conf. Recommender Syst.*, Sep. 2019, pp. 506–510.

[128] D. Chao, L. Kaili, Z. Jing, and J. Xie, "Collaborative filtering recommendation algorithm classification and comparative study," in *Proc. 4th Int. Conf. Distance Educ. Learn.*, May 2019, pp. 106–111.

[129] O. Vélez-Langs and I. Caicedo-Castro, "Recommender systems for an enhanced mobile e-learning," in *Proc. Int. Conf. Hum.-Comput. Interact.* Cham, Switzerland: Springer, 2019, pp. 357–365.

[130] H. Hajri, 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.

[131] N. M. Ndiyae, Y. Chaabi, K. Lekdioui, 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.

[132] A. S. Lan, J. 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.

[133] S. Assami, N. Daoudi, and R. Ajhoun, "Ontology-based modeling for 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.

[134] A. Chanaa and N.-E. El Faddouli, "Context-aware factorization machine for recommendation in massive open online courses(MOOCs)," in *Proc. Int. Conf. Wireless Technol., Embedded Intell. Syst. (WITS)*, Apr. 2019, pp. 1–6.

[135] L. Singelmann, E. Swartz, M. Pearson, R. Striker, and E. A. Vazquez, "Design and development of a machine learning tool for an innovation-based learning MOOC," in *Proc. IEEE Learn. With MOOCS (LWMOOCS)*, Oct. 2019, pp. 105–109.

[136] B. Faqihi, 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.

[137] S. Sakboonyarat and P. Tantatsanawong, "Massive open online courses (MOOCs) recommendation modeling using deep learning," in *Proc. 23rd Int. Comput. Sci. Eng. Conf. (ICSEC)*, Oct. 2019, pp. 275–280.

[138] K. Elghomary and D. Bouzidi, "Dynamic peer recommendation 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.
[139] 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 Accessibility (ICTA)*, Dec. 2019, pp. 1–6.
[140] S. Assami, N. Daoudi, and R. Ajhoun, "Exploring social media data for MOOC recommendation," in *Proc. Int. Conf. Syst. Collaboration Big Data, Internet Things Secur. (SysCoBIoTS)*, Dec. 2019, pp. 1–8.
[141] 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.
[142] 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.
[143] S. R. Nangi, Y. Kanchugantla, P. G. Rayapati, and P. K. Bhowmik, "OffVid: 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.
[144] F. Fazuludeen, G. Vijayakumaran, Z. A. Mahroof, N. Kodagoda, and K. Suriyawansa, "MOOCRec 2 for humanities-learning style based MOOC recommender and search engine," in *Proc. Int. Conf. Advancements Comput. (ICAC)*, Dec. 2019, pp. 470–475.
[145] T. Xia, "An e-learning support middleware with MOOC course recommendation," in *Proc. 14th Int. Conf. Comput. Sci. Educ. (ICCSE)*, Aug. 2019, pp. 596–600.
[146] A. Tripathi, T. S. Ashwin, and R. M. R. Guddeti, "EmoWare: A context-aware framework for personalized video recommendation using affective video sequences," *IEEE Access*, vol. 7, pp. 51185–51200, 2019.
[147] Q. Lu and J. Xia, "Research on the application of item-based collaborative filtering algorithms in MOOC," in *Proc. J. Phys., Conf.*, 2019, vol. 1302, no. 3, Art. no. 032020.
[148] H. Liu and X. Li, "Learning path combination recommendation based on the learning networks," *Soft Comput.*, vol. 24, no. 6, pp. 4427–4439, Mar. 2020.
[149] P. Cao and D. Chang, "A novel course recommendation model fusing content-based recommendation and K-means clustering for Wisdom education," in *Proc. LISS*. Singapore: Springer, 2020, pp. 789–809.
[150] S. Assami, N. Daoudi, and R. Ajhoun, "A semantic recommendation system for learning personalization in massive open online courses," *Int. J. Recent Contrib. Eng., Sci. IT (iJES)*, vol. 8, no. 1, p. 71, Mar. 2020.
[151] Y. Benjelloun Touimi, A. Hadioui, N. El Faddouli, and S. Bennani, "Intelligent chatbot-LDA recommender system," *Int. J. Emerg. Technol. Learn. (iJET)*, vol. 15, no. 20, p. 4, Oct. 2020.
[152] M. Zhang, S. Liu, and Y. Wang, "STR-SA: Session-based thread recommendation for online course forum with self-attention," in *Proc. IEEE Global Eng. Educ. Conf. (EDUCON)*, Apr. 2020, pp. 374–381.
[153] X. Zhao and B. Liu, "Application of personalized recommendation technology in MOOC system," in *Proc. Int. Conf. Intell. Transp., Big Data Smart City (ICITBS)*, Jan. 2020, pp. 720–723.
[154] J. Wang, H. Xie, O. T. S. Au, D. Zou, and F. L. Wang, "Attention-based CNN for personalized course recommendations for MOOC learners," in *Proc. Int. Symp. Educ. Technol. (ISET)*, Aug. 2020, pp. 180–184.
[155] B. Mondal, O. Patra, S. Mishra, and P. Patra, "A course recommendation system based on grades," in *Proc. Int. Conf. Comput. Sci., Eng. Appl. (ICCSEA)*, Mar. 2020, pp. 1–5.
[156] R. Sankalpa, T. Sankalpani, T. Sandeepani, N. Ransika, N. Kodagoda, and K. Suriyawansa, "MOOCs recommender based on user preference and video quality," in *Proc. 2nd Int. Conf. Advancements Comput. (ICAC)*, Dec. 2020, pp. 79–84.
[157] J. Liu, H. Zhang, and Z. Liu, "Research on online learning resource recommendation method based on wide & deep and elmo model," in *Proc. J. Phys., Conf.*, 2020, vol. 1437, no. 1, Art. no. 012015.
[158] S. Yin, K. Yang, and H. Wang, "A MOOC courses recommendation system based on learning behaviours," in *Proc. ACM Turing Celebration Conf. (China)*, May 2020, pp. 133–137.
[159] R. Campos, R. P. dos Santos, and J. Oliveira, "A recommendation system based on knowledge gap identification in MOOCs ecosystems," in *Proc. XVI Brazilian Symp. Inf. Syst.*, Nov. 2020, pp. 1–8.
[160] H. Sebbaq, N.-E. el Faddouli, and S. Bennani, "Recommender system to support MOOCs teachers: Framework based on ontology and linked data," in *Proc. 13th Int. Conf. Intell. Syst.: Theories Appl.*, 2020, pp. 1–7.
[161] H. Slimani, O. Hamal, N.-E. El faddouli, S. Bennani, and N. Amrous, "The hybrid recommendation of digital educational resources in a distance learning environment: The case of MOOC," in *Proc. 13th Int. Conf. Intell. Syst.: Theories Appl.*, 2020, pp. 1–9.
[162] J. Gong, S. Wang, J. Wang, W. Feng, H. Peng, J. Tang, and P. S. Yu, "Attentional graph convolutional 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.
[163] 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.
[164] F. Fauzan, D. Nurjanah, and R. Rismala, "Apriori association rule for course recommender system," *Indonesian J. Comput. (Indo-JC)*, vol. 5, no. 2, pp. 1–16, 2020.
[165] T. Le, V. 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. (CGVCVIP)*, 2020, pp. 141–148. [Online]. Available: https://www.cgv-conf.org/
[166] C. Gusmão, J. Machiavelli, and P. Mendes. *Model for Content Recommendation in Massive Open Online Courses: Motivational Actions in a Forum*. [Online]. Available: https://wcol2019
[167] A. Khalid, K. Lundqvist, A. Yates, and M. A. Ghzanfar, "Novel online recommendation algorithm for massive open online courses (NoR-MOOCs)," *PLoS ONE*, vol. 16, no. 1, Jan. 2021, Art. no. e0245485.
[168] L. Wu, "Collaborative filtering recommendation algorithm for MOOC resources based on deep learning," *Complexity*, vol. 2021, Apr. 2021, Art. no. 5555226.
[169] N. González-Castro, P. J. Muñoz-Merino, C. Alario-Hoyos, and C. Delgado Kloos, "Adaptive learning module for a conversational agent to support MOOC learners," *Australas. J. Educ. Technol.*, vol. 37, no. 2, pp. 24–44, May 2021.
[170] N. T. Son, J. Jaafar, I. A. Aziz, and B. N. Anh, "Meta-heuristic algorithms for learning path recommender at MOOC," *IEEE Access*, vol. 9, pp. 59093–59107, 2021.
[171] *HarvardX-MITx Person-Course Academic Year 2013 De-Identified Dataset, Version 2.0. Harvard Dataverse (2014)*, HX MITx, HarvardX MITx, Harvard Dataverse, Online Repository, 2014. [Online]. Available: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/26147
[172] A. Ho, J. Reich, S. Nesterko, and D. Seaton, "HarvardX and MITx: The first year of open online courses, fall 2012-summer 2013," HarvardX MITx, Work. Paper 1, 2014. [Online]. Available: http://ssrn.com/abstract=2381263
[173] ShareCourse. (2015). *Introduction to Computer Networks*. [Online]. Available: http://sharecourse.net/sharecourse/course/view/courseInfo/568
[174] F. Bouchet and R. Bachelet, "Do MOOC students come back for more? Recurring students in the GdP MOOC," in *Proc. Eur. MOOCs Stakeholders Summit*, 2015, pp. 174–182.
[175] Keggle. (2016). *StackSample: 10% of Stack Overflow Q & A (Version 1 ed.)*. [Online]. Available: https://www.kaggle.com/stackoverflow/stacksample/version/1
[176] P. A. A. Akshay. (2014). *The Stanford MOOCPosts Data Set*. [Online]. Available: https://datastage.stanford.edu/StanfordMoocPosts/
[177] W. Jiang, Z. A. Pardos, and Q. Wei, "Goal-based course recommendation," in *Proc. 9th Int. Conf. Learn. Anal. Knowl.*, Mar. 2019, pp. 36–45.
[178] D. Dessì, G. Fenu, M. Marras, and D. R. Recupero, "COCO: Semantic-enriched collection of online courses at scale with experimental use cases," in *Proc. World Conf. Inf. Syst. Technol.* Springer, 2018, pp. 1386–1396.
[179] E. Kim. (Oct. 25, 2018). *If Personalized Learning is the Journey, Then Adaptive Learning is the Waze App*. [Online]. Available: https://elmlearning.com/personalized-learning-vs-adaptive-learning/
[180] J. Downs. (Oct. 25, 2017). *What's the Difference Between Personalized and Adaptive Learning?*. [Online]. Available: https://www.lrnr.us/blog/whats-the-difference-between-personalized-and-adaptive-learning/
[181] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," *Eng. Educ.*, vol. 78, no. 7, pp. 674–681, 1988.
[182] D. M. Blei and J. D. Lafferty, "Topic models," in *Text Mining*. Boca Raton, FL, USA: CRC Press, 2009, pp. 101–124.

[183] Y.-S. Tsai. (2021, 30 Jan. 2021). *What is Learning Analytics?*. [Online]. Available: https://www.solaresearch.org/about/what-is-learning-analytics/#:~:text=LEARNING%20ANALYTICS%20is%20the%20measurement,even%20as%20the%20field%20has

[184] J. Hauer and T. Quill, "Educational needs assessment, development of learning objectives, and choosing a teaching approach," *J. Palliative Med.*, vol. 14, no. 4, pp. 503–508, Apr. 2011.

[185] W. Reisig, *A Primer in Petri Net Design*. Berlin, Germany: Springer-Verlag, 2012.

[186] I. Palomares, C. Porcel, L. Pizzato, I. Guy, and E. Herrera-Viedma, "Reciprocal recommender systems: Analysis of state-of-art literature, challenges and opportunities towards social recommendation," *Inf. Fusion*, vol. 69, pp. 103–127, May 2021.

[187] J.-W. Han, J.-C. Jo, H.-S. Ji, and H.-S. Lim, "A collaborative recommender system for learning courses considering the relevance of a learner's learning skills," *Cluster Comput.*, vol. 19, no. 4, pp. 2273–2284, 2016.

[188] G. Docs. (Oct. 25, 2020). *Collaborative Filtering Advantages & Disadvantages*. [Online]. Available: https://developers.google.com/machine-learning/recommendation/collaborative/summary

[189] R. Yera and L. Martínez, "A recommendation approach for programming online judges supported by data preprocessing techniques," *Appl. Intell.*, vol. 47, no. 2, pp. 277–290, 2017.

[190] U. Shardanand and P. Maes, "Social information filtering: Algorithms for automating 'word of mouth,'" in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, 1995, pp. 210–217.

[191] P. Lops, M. De Gemmis, and G. Semeraro, "Content-based recommender systems: State of the art and trends," in *Recommender Systems Handbook*. Boston, MA, USA: Springer, 2011, pp. 73–105.

[192] G. Docs. (Oct. 25, 2020). *Content-Based Filtering Advantages & Disadvantages*. [Online]. Available: https://developers.google.com/machine-learning/recommendation/content-based/summary

[193] R. Burke, "Hybrid recommender systems: Survey and experiments," *User Model. User-Adapted Interact.*, vol. 12, no. 4, pp. 331–370, Nov. 2002.

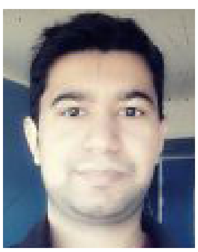
[194] I. Horrocks, "Ontologies and the semantic web," *Commun. ACM*, vol. 51, no. 12, pp. 58–67, 2008.

[195] L. IMS, *IMS. IMS Learning Design Information Model*, IMS Global Learning Consortium, Lake Mary, FL, USA, 2003.

[196] J. Brooke, P. Jordan, B. Thomas, B. Weerdmeester, and I. McClelland, *Usability Evaluation in Industry*. Boca Raton, FL, USA: CRC Press, 1996.

[197] B. Parsia and E. Sirin, "Pellet: An owl dl reasoner," in *Proc. 3rd Int. Semantic Web Conf.-Poster*, vol. 18, 2004, p. 13.

IMRAN UDDIN received the master's degree in computer science from The University of Agriculture Peshawar, in 2019. He is currently pursuing the Ph.D. degree with Islamia College University Peshawar. He has been a Lecturer with the Department of ICS/IT, The University of Agriculture Peshawar, since 2001. Apart from teaching, he has been working as a freelance developer, since 1999. His interests include deep learning, web semantics, machine learning, and natural language processing.



ALI SHARIQ IMRAN (Member, IEEE) received the master's degree in software engineering and computing from the National University of Science and Technology (NUST), Pakistan, in 2008, and the Ph.D. degree in computer science from the University of Oslo (UiO), Norway, in 2013. He is currently an Associate Professor with the Department of Computer Science, Norwegian University of Science and Technology (NTNU), Norway. He has over 65 peer-reviewed journals and conference publications to his name. He specializes in applied research focusing on deep learning technology and its application to signal processing, natural language processing, and the semantic web. He is a member of the Norwegian Colour and Visual Computing Laboratory (Colourlab) and the IEEE Norway Section. He has served as a reviewer for many reputed journals over the years.

KHAN MUHAMMAD (Member, IEEE) received the Ph.D. degree in digital contents from Sejong University, Seoul, South Korea, in 2019. He is currently an Assistant Professor with the Department of Interaction Science and the Director of the Visual Analytics for Knowledge Laboratory (VIS2KNOW Lab), Sungkyunkwan University, Seoul. His research interests include intelligent video surveillance (fire/smoke scene analysis, transportation systems, and disaster management), medical image analysis, (brain MRI, diagnostic hysteroscopy, and wireless capsule endoscopy), information security (steganography, encryption, watermarking, and image hashing), video summarization, multimedia data analysis, computer vision, the IoT/IoMT, and smart cities. He is serving as a reviewer for over 100 well-reputed journals and conferences, such as IEEE, ACM, Springer, Elsevier, Wiley, SAGE, and Hindawi publishers. He is also an associate editor of six journals and an editorial board member of seven journals.

NOSHEEN FAYYAZ received the master's degree from the Department of Computer Science, University of Peshawar, Pakistan, in 2000, and the M.S. degree in computer science from the Institute of Business and Management Sciences, The University of Agriculture Peshawar, in 2010. She is currently pursuing the Ph.D. degree at University of Peshawar. She is currently a Lecturer with the Department of Computer Science, University of Peshawar. She has been teaching for 20 years. Her research interests include web semantics, document analysis, accessibility, information overload, cross domains, ontologies, and linked open data.

MUHAMMAD SAJJAD received the master's degree from the Department of Computer Science, College of Signals, National University of Sciences and Technology, Rawalpindi, Pakistan, in 2012, and the Ph.D. degree in digital contents from Sejong University, Seoul, South Korea, in 2015. He is currently working as an ERCIM Research Fellow at NTNU, Norway. He is also an Associate Professor with the Department of Computer Science, Islamia College Peshawar University, Pakistan. He is also the Head of the Digital Image Processing Laboratory, Islamia College University Peshawar, where many students are involved in different research projects under his supervision, such as big data analytics, medical image analysis, multi-modal data mining and summarization, image/video prioritization and ranking, fog computing, the Internet of Things, autonomous navigation, and video analytics. He has published more than 65 papers in peer-reviewed international journals and conferences. His primary research interests include computer vision, image understanding, pattern recognition, robotic vision, and multimedia applications, with current emphasis on economical hardware and deep learning, video scene understanding, activity analysis, fog computing, the Internet of Things, and real-time tracking. He is serving as a professional reviewer for various well-reputed journals and conferences. He is an Associate Editor of IEEE Access and acting as a Guest Editor of IEEE Transactions on Intelligent Transportation Systems.