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# A Comprehensive Review of Course Recommendation Systems for MOOCs

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**Abstract:** In recent years, many students have accepted Massive Open Online Courses (MOOCs) as a means of education. Due to the enormous number of courses available through MOOC, students need help in identifying and selecting an appropriate course based on their profile and interests. To address this issue, MOOCs incorporate a course recommendation system that generates a list of courses based on the student's prerequisites. This literature review attempts to detect and assess trends, processes employed, and developments in MOOC course RS through an exhaustive analysis of academic literature published between January 1, 2016, and November 31, 2023. The study includes the various methodologies employed, the datasets used for evaluations, the performance measures used, and the many issues encountered by Recommendation Systems. Literature published in ScienceDirect, Wiley, Springer, ACM, and IEEE, were chosen for review. After applying inclusion and exclusion criteria, 76 articles from the aforementioned databases, including journals, conferences, and book chapters, were selected. The investigation found that methods from Machine Learning and Deep Learning were widely deployed. Traditional approaches like "content-based filtering, collaborative filtering, and hybrid filtering" were frequently employed in conjunction with other algorithms for more accurate and precise suggestions. It also underlines the need to take data sparsity, the cold start problem, data overload, and user preferences into account when designing a course recommendation system. This paper contributes to examining the cutting-edge course Recommendation System in depth, examining recent developments, difficulties, and future work in this field.

**Keywords:** Recommendation Systems, Massive Online Open Courses, Content based Reccomendation system, Collaborative based Recommendation system, Machine Learning

## 1. INTRODUCTION

This study conducts a systematic review of literature on Course Recommendation Systems for Massive Open Online Courses (MOOCs) from various academic sources, aiming to inform future research.

### A. *MOOCs(Massive Open Online Courses:)*

In 2008, Stephen Downes and George Siemens of the University of Manitoba launched an online course called "Connectivism and Connective Knowledge," which attracted over 2,200 students. Since then, MOOCs have become a popular trend as e-learning platforms, allowing unlimited access to courses without limiting the number of students[1].Various strategies are used to manage MOOCs, such as connection MOOCs (cMOOCs), which are defined on the loosely developed connection theory, and content-based MOOCs(xMOOCs), which employ a more cognitive approach[2]. Massive Open Online Courses (MOOCs) have significantly advanced in online learning and distance education due to their global reach and freedom of participation, setting them apart from standard e-learning platforms that have restrictions[3]. Massive Open Online Courses (MOOCs) offer students free access to entire courses, assignments, and lecturers. Students who excel receive certificates, which can be used to build a strong resume and showcase skills on professional networks[4]. MOOCs have significantly impacted the education sector by providing essential skills to underserved groups, increasing access to quality education, and encouraging innovation, presenting new possibilities and challenges[5]. In 2021, over 220 million students registered for courses on platforms like Coursera, edX, and MOOCs, with 40 million registrations, except for China enrollments. The University of Toronto's MOOC Impact Report for 2023 shows 4,200,000 students from 182 countries, earning nearly 300,000 course certifications. Challenges include cheating, obtaining academic admissions certificates, and showcasing skills in professional social networks[4], lack of attention towards the needs and expertise of the teacher[5], unable to offer proper courses in some technical course like computing to be specific in computer science stream[6], negligence on the personalized needs of the students[7].

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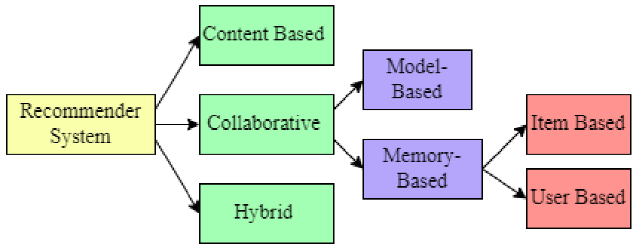


Figure 1. Classification of the Recommender System

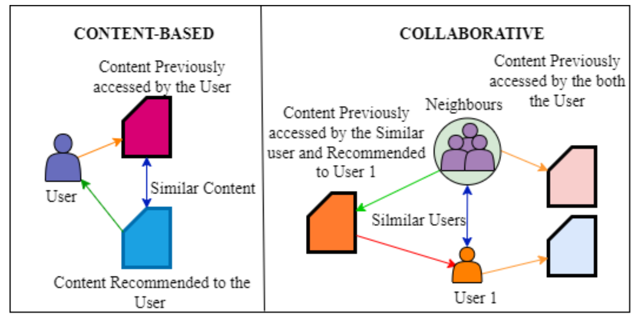


Figure 2. Content-Based and Collaborative RS

*B. Recommendation Systems:*

Recommendation Systems use data from various sources to identify client preferences, with the user acting as the recipient and the recommended item as the product. Knowledge-based systems provide recommendations based on user-defined criteria, enabling more accurate predictions of future choices[8].Currently, recommender systems are seeing increased use in a wide range of applications, including medical sciences[9], Agriculture[10], online learning[7], tourism[11], movies[12], music[13], online shopping[14], news[15], specialized academic resources[16], etc. Recommender Systems fall into three categories:content-based, collaborative, and hybrid. Figure 1 demonstrates the classification of the Recommender System.

*1) Content-Based*

As shown in Figure 2, content-based RS employ personal user characteristics such as gender, age, and social media activities to anticipate their choices without referring to information about other individuals[17],[18]. Knowledge filtering tasks remove unwanted data from incoming streams, using item semantics and Information Retrieval concepts. Recommendations are created by comparing item content to an individual's profile, with associated weights, and this simple, efficient strategy has proven useful in classic Information Retrieval models.

*2) Collaborative Recommendation System*

Figure 2 shows a collaborative recommendation system that uses data to suggest content to a user based on their interests and preferences. The system calculates the user's resemblance to others, determining the effectiveness of the method based on the strength of the association between users or items[18],[19],[20]. A collaborative recommendation system assigns users to identical neighbors, who choose items based on their neighborhood's views. These systems can be categorized into memory-based (neighborhood-based or heuristic-based) and model-based techniques[21].

*a) Model-Based*

The model-based method involves incorporating ratings into predictions, using data collected from ratings to build a prediction model. The goal is to simulate user-item interactions using variables reflecting individual preferences and item classification. The model is trained on the current dataset and used to forecast user ratings for new products[17].There are many model-based approaches, including Latent Semantic Analysis, Singular Value Decomposition, and Bayesian Clustering Singular Value Decomposition.

*b) Memory-Based:*

Memory-based methods use user-item ratings to anticipate categorization for new items, excelling in precision. Model-based methods are more efficient for large datasets. Classification can be done using user-based and item-based recommendations[18],[22].

*c) User-Based method:*

The user-based method filters incoming items based on ratings from previous community members who have assessed similar products. Users with similar interests are immediately recommended to others, creating a matrix of similarity ratings between users[20],[22].Consequently, the current user's rating of an item will be estimated according to the likes and dislikes of comparable neighbors.

*d) Item-Based method:*

The item-based method uses the items and Items matrix to store similarity ratings between items, suggesting goods most comparable to a collection of items with high ratings from the current user[18],[22]. The expected rating is established by the extent of similarity between an item and adjacent items, with a higher level of similarity resulting in a closer rating[23].

*3) Hybrid Recommendation System:*

The drawbacks of both collaborative and content-based methods can be overcome by combining them into a single hybrid approach[24].Richa Sharma[20] utilized a hybrid method to enhance performance, which involves analyzing user profiles to identify similar individuals and calculating similarity using the cosine equation based on user ratings, as illustrated in Figure 3[23]. Over the past two decades, researchers have developed recommendation algorithms using collaborative filtering and big data association rule mining. These algorithms determine similar users, select items based on user profiles, and offer desired items[25], RS for e-learning incorporating ontology and sequential pattern mining[26], a multi-criteria clustering approach[27], a hybrid collaborative filtering model with deep structure[28], combining similarity models with Markov chains[23],[29],and more.

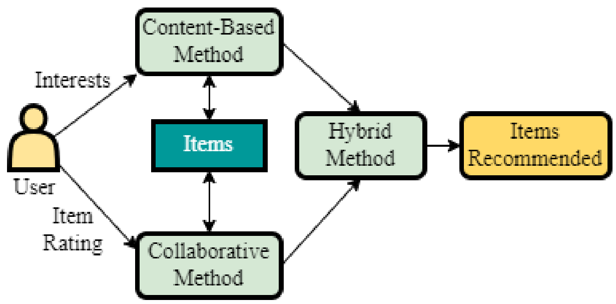


Figure 3. Hybrid Recommendation System

### C. Recommendation System for MOOCs:

MOOCs collect data on learners' interests, activities, and course enrollments, which are used by recommender systems to provide personalized suggestions. These systems aim to streamline the process by utilizing user community perspectives and preferences, using collaborative filtering, content-based recommendation, or hybrid approaches[30]. Recommender systems in MOOCs aid users in finding suitable learning resources, enhancing MOOC design, converting traditional courses into internet-based formats, and analyzing student learning patterns[31]. The shift towards a more diverse educational model in MOOCs is hindered by a lack of skills to provide personalized experiences to diverse audiences[32]. The rapid growth of MOOC data presents challenges for users in selecting suitable courses for professional and educational growth. Course recommendations can help address this issue, but RS faces issues like data sparsity, anti-internet elements, and clod start while suggesting courses[31]. Machine learning and deep learning approaches, such as Latent Dirichlet Allocation (LDA) and K-mean clustering and Apriori algorithms, are being proposed to improve RS for MOOC learners[33],Courses Recommendation System Based on Learning Behaviours[7] Case Based Reasoning(CBR) techniques[34],Collaborative and Hybrid Filtering[28],[35],[36]etc. Research on recommendations primarily focuses on direct connection links, limiting the effectiveness of information representation and resulting in decreased recommendation quality and performance. The frequent sharing of information within social circles suggests that user preferences can be influenced by these networks[**?**]. The current state-of-the-art MOOCs Course RS utilize various machine learning and deep learning algorithms and frameworks to address the issues.

The study analyzed recommender systems in MOOCs from 2015-2023, focusing on English-language publications, to observe trends and explore unexplored categories, providing a comprehensive understanding of these systems.

## 2. METHOD

### A. Review Method

The study utilized a Systematic Literature Review (SLR) to analyze MOOC Course Recommendation, a systematic method for identifying, evaluating, and interpreting research findings[37].Figure 4 provides a more comprehensive view.

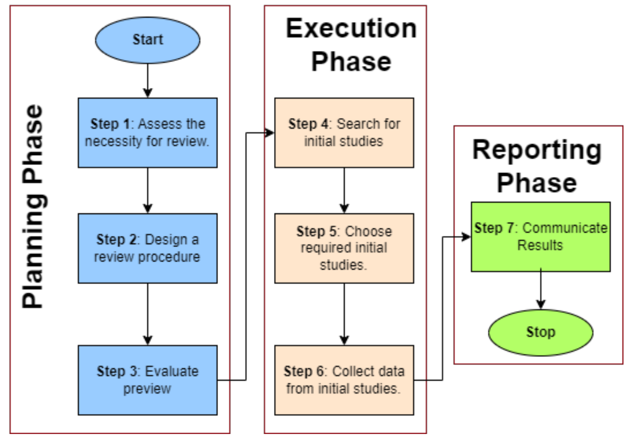


Figure 4. Systematic Literature Review (Okoli and Schabram, n.d.)

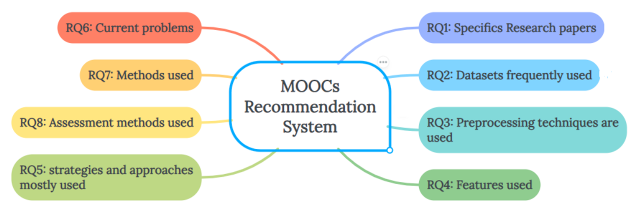


Figure 5. Mind Map of Review of MOOCs RS

### B. Research Question (RQ)

Research Questions (RQ) enhance review process by focusing on concentration and consistency, often using "PICOC criteria (Population, Intervention, Comparison, Outcomes, and Context)"[38], which are listed in Table I.The mind map displayed in Figure 5 serves as a demonstration used in understanding research questions about the literature evaluation of RS for MOOCs.

TABLE I. PICOC CRITERIA

| | |
|---|---|
| Population | MOOCS Course Recommendations |
| Intervention | Methods used in MOOCs Course Recommendations |
| Comparison | With existing systems traditional systems |
| Outcomes | Performance evaluation of MOOCs Course RS |
| Context | Research using online available datasets to provide better course recommendation |

### C. Search Strategies

The data for this analysis of MOOC RS was gathered from articles available on sciencedirect.com, ieeexplore.ieee.org,dl.acm.org[39],and other academic databases of prestigious journals. To find articles relevant to the issue,the search entailed inputting particular keywords or synonyms related to the research topic.The search term used for this paper retrieval procedure was (MOOCs course recommendation system OR Course Recommendation System OR e-learning course

TABLE II. RESEARCH QUESTION AND MOTIVATION

| ID | Research Questions | Motivation |
|---|---|---|
| RQ1 | Which journal or conference paper regarding MOOCs RS? | Recognize key research papers on RS on MOOCs. |
| RQ2 | Which datasets are used in MOOCs RS | Recognize datasets frequently employed in RS for MOOCs |
| RQ3 | What preprocessing techniques are employed in MOOCs RS? | Recognize preprocessing techniques are employed in RS for MOOCs |
| RQ4 | Which characteristics are used in MOOCs RS? | Recognize characteristics are used in MOOCs RS |
| RQ5 | What strategies and approaches do MOOC RS use? | Recognize strategies and approaches mostly used by MOOC RS |
| RQ6 | What are the current issues with MOOC RS? | Recognize current issues in MOOC RS |
| RQ7 | What approach and techniques are used in MOOC RS? | Recognize the approaches and techniques used in MOOC RS |
| RQ8 | What assessment methodologies are used in MOOC RS? | Recognize the assessment methodologies used in MOOC RS |

TABLE III. INCLUSION AND EXCLUSION CRITERIA

| | |
|---|---|
| Inclusion Criteria | • Articles published in Journals and conferences of high impact<br>• Articles that have a well-defined motive, methodology, experimentation and results<br>• Articles which are relevant to the MOOCs Course RS<br>• Articles that have a well-defined motive, methodology |
| Exclusion Criteria | • Research that excludes experimental outcomes and relies on unclear datasets<br>• Studies that go beyond MOOC RS's Scope<br>• Research papers written in languages other than English<br>• Unpublished studies<br>• Review or survey articles |

recommendation system OR course recommender systems) AND (approach, methodology, or method).

The search phrase is optimized for title, abstract, and keywords, with adjustments made to meet the specific requirements of each database on individual sites[39]. The literature evaluation began in 2015 due to a significant increase in research activity on this particular topic.

This review study examines various publications, including journal articles, conference proceedings, and book chapters, to identify potential insights from conferences or continuing paper articles[39]. Papers only in the English language are considered.

### D. Study Selection

The paper article search phase involves selecting multiple papers that meet requirements using an adjustment procedure. The criteria for incorporating paper articles in primary research are organized into five sections: keywords, period, sources, publishing format, and work category. Keywords are used to identify relevant published material from specific sources, while the timeframe relates to the actual era of article release.

The 'publishing format' refers to the type of publication,

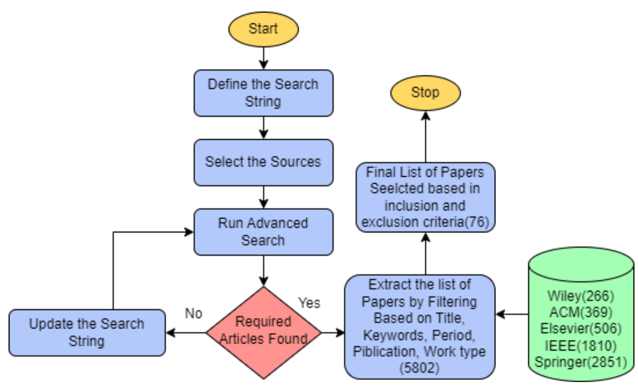


Figure 6. Search and Selection Mechanism

like conference papers or journal articles, while 'work category' describes the type of work mentioned in the article, like implementation, analysis, or proposal. Figure 6 illustrates a process for selecting relevant paper articles for further review.

### E. Data Extraction

The data extraction phase involves collecting data from the primary study to address research inquiries.The data extraction table used is outlined in Table IV.

TABLE IV. ACQUIRING DATA

| Research Question | Attribute |
|---|---|
| RQ1 | Publications |
| RQ2 | Datasets of MOOCs |
| RQ3 | Preprocessing of MOOC datasets |
| RQ4 | Features of MOOCs RS |
| RQ5 | MOOCs RS strategies and techniques |
| RQ6 | Problems with current MOOCs RS |
| RQ7 | Techniques used in MOOC RS |
| RQ8 | Evaluation methods used in MOOC RS |

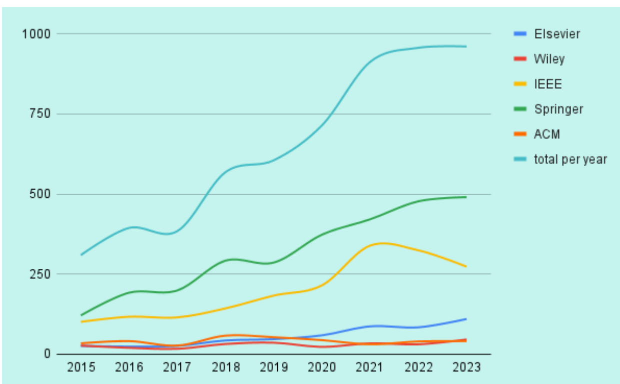


Figure 7. Publications in Journals and Conferences

TABLE V. NUMBER OF ARTICLES PUBLISHED FROM 2015-2023

| Publisher | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
| Science Direct | 26 | 24 | 26 | 43 | 47 | 59 | 87 | 84 |
| Wiley | 27 | 20 | 17 | 32 | 36 | 23 | 34 | 31 |
| IEEE | 101 | 117 | 115 | 143 | 183 | 215 | 339 | 324 |
| Springer | 121 | 192 | 199 | 292 | 286 | 373 | 421 | 477 |
| ACM | 34 | 41 | 27 | 58 | 53 | 44 | 31 | 40 |

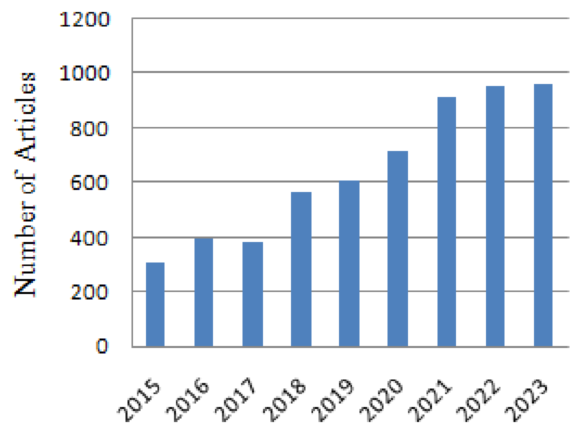


Figure 8. Total Papers Published per year

## 3. FINDINGS

### A. *Publication of paper studies*

Between 2015 and 2023, around 6000 publications on online learning platforms, primarily MOOCs, were published in prestigious journals and conferences. The annual distribution of articles indicates an increasing trend in research on MOOC course recommendations, indicating significant opportunities for future study. This trend is a result of the transition from traditional classrooms to online learning platforms. Figure 7 and Figure 8 depicts the annual trend of articles published on MOOCs recommendation system.

The study selected 76 papers for further review based on Table III's inclusion and exclusion criteria[40].After filtering articles in Google Scholar, the researchers identified 76 papers from five academic databases: ScienceDirect, Springer, IEEE, ACM, and Wiley. Figure 9 shows the year-wise distribution of selected articles from these databases.

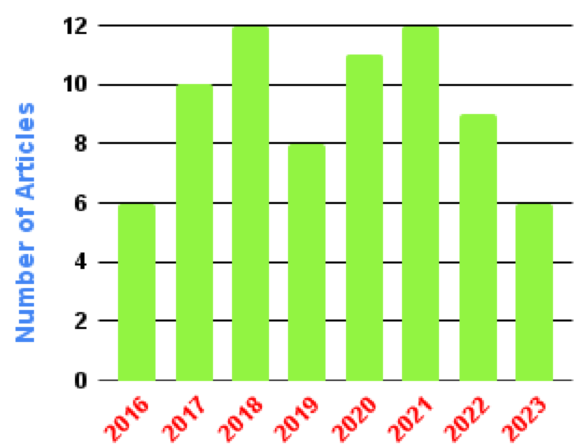


Figure 9. Yearwise Distribution of Selected Articles

We have researched a variety of scholarly sources.

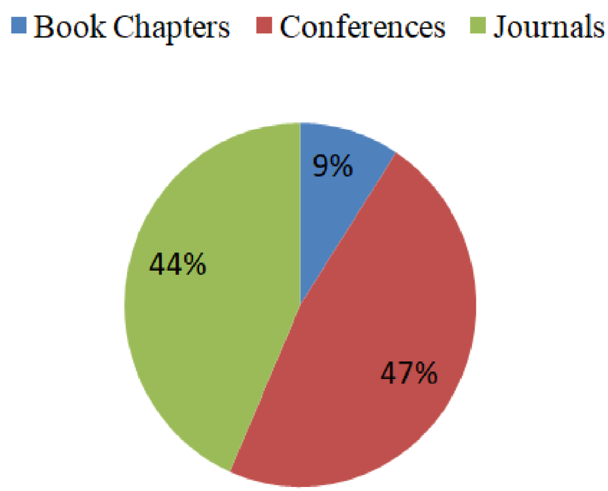


Figure 10. Distribution of Type of Papers

Specifically, we examined content from 7 book sections, 36 conferences, and 33 scholarly journals contributing 9%, 47% and 44% respectively, with a significant percentage of articles from Springer, various journals, and conference proceedings. Figure 10 shows the distribution of articles published in conferences, journals, and book chapters.

## B. Dataset

Course RS for MOOCs heavily relies on datasets for development and assessment, including data about learners, courses, interactions, and other relevant aspects. These datasets often include student characteristics, course descriptions, subjects covered, difficulty levels, and ratings, as well as interaction data like learner-course exchanges, evaluations, and completion status.

The study of MOOC course recommendation (RS) employs datasets from various sources, including colleges, universities, educational websites, and research programs. Popular MOOC platforms like Coursera, edX, and XuetangX are used to investigate course suggestions, experiment with alternative algorithms, and assess RS performance. The XuetangX dataset, a Chinese MOOC platform, is the most frequently used in course recommendation methods design.

Other datasets contribute to numerous publications, but their individual use is limited. The majority of research is conducted on publicly available datasets from platforms like Coursera, edX, and XuetangX.

The other data set like Facebook[41], "European Expert Network on Economics of Education (EENEE")[42], "Network of Experts on Social Aspects of Education and Training(NESET)"[42], Canvas[34], Classroom data[43], university data[44], iCourse[7],[45], Khan Academy[30],[46],[47], kaggle[48], Udacity[24], [47], MovieLens[49][50][51], MOOCCourse[52],[53], MOOCCube[52],[53],[54],[55], [56], Coursetalk[35],[57] are to name a few that were used in different articles.

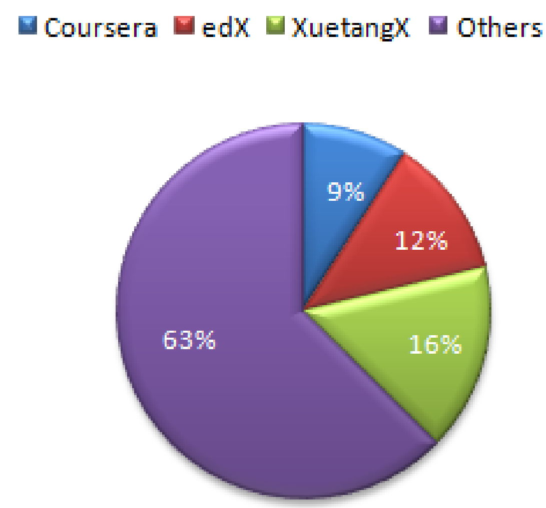


Figure 11. Distribution of Datasets Used in Articles

Figure 11 show the distribution of different datasets used in the different articles.

Addressing issues like data sparsity, heterogeneity, and scalability is crucial for the robustness and reliability of the RS created when dealing with large datasets[58].

Course recommendation systems (CRS) for MOOCs primarily utilize Machine Learning methods, with a growing trend towards Deep Learning for improved accuracy and precision. Various algorithms, both classic and bespoke, have been employed for MOOC RS construction, with Table VII illustrating their growth trends.

## C. Topics or Trend Research

Our systematic literature review identified various MOOC-specific RS, including Concept RS, Course RS, Exercise RS, Learning Materials RS, Learning Paths RS, Next Step RS, and Thread RS[59]. Table VI displays the distribution of publications based on the recommendations discussed in this review report, with each type contributing to up to three study subjects.

The study reveals that collaborative filtering is primarily used in the development of RS for MOOCs, alongside powerful Machine Learning and Deep Learning algorithms, to enhance recommendation efficiency.

## D. Approach techniques

Researchers frequently use Machine Learning and Deep Learning methodologies in their research compared to other identified approaches.

### 1) Machine Learning Approaches

MOOC course RS utilizes Machine Learning to offer personalized suggestions based on large data sets, including

TABLE VI. DISTRIBUTION OF THE ARTICLES BASED ON THE TYPE OF RS

| Recommendation System (RS) | No of articles |
|---|---|
| Course RS | 68 |
| Next-Step RS | 1 |
| Exercise RS | 3 |
| Concept RS | 1 |
| Learning Material RS | 1 |
| Thread RS | 1 |
| learning path RS | 1 |

user actions, course material, and comments. This helps assess students' learning behavior and registration patterns, but scalability is a challenge due to increasing student diversity.

Some of the approaches using machine learning methods are discussed below.

The increasing number of Massive Open Online Course (MOOC) providers like Coursera, edX, Udemy, XuetangX, and Nptel is making it challenging to find suitable learning materials. To overcome this problem, the authors of the paper[41] developed MOOCBuddy, a chatbot on Facebook Messenger that uses user profiles and interests to recommend learning materials, using real-time click stream data and a machine learning model based on behavioral patterns[32]

In[34] the authors developed a MOOC course recommendation system using a revolutionary information retrieval technique and a Case-Based Reasoning approach, evaluating student profiles, needs, and learning history to identify relevant courses for individual students.

A content-aware architecture improves efficiency by extracting personalized student information, leveraging demographics and course prerequisites. A course recommendation algorithm is developed, blending user preferences and requirements[31].

In[60] a professional MOOC recommendation system is introduced that uses data mining to classify active and passive learners, achieving an average accuracy of 92% for course suggestions.

The study analyzes students' online learning behaviors to enhance personalized recommendations in MOOC courses. It combines information from multiple sources and presents two models, one based on each source and one integrating them[7].

A study developed a recommendation system to assist students in selecting suitable modules or courses within MOOC environments. Topic modeling, specifically "Non-negative Matrix Factorization" (NMF), was used to identify commonalities across different providers. A content-based recommendation engine then made recommendations based on data from various sites[30].

In[61],[62], Researchers have developed a recommendation model for Massive Open Online Courses (MOOCs) that uses Deep Learning and a "Multilayer Perceptron" (MLP) architecture for large data processing. The model adheres to the "Cross-industry Standard Process for Data Mining" (CRISP-DM) and has seven hidden layers, a 1e-3 learning rate, and GPU acceleration across 250 epochs. Performance is assessed using precision calculations.

Reciprocal recommender systems are crucial in online services like dating, recruiting, social networking, learning, and skill-sharing. They propose users to each other, requiring satisfaction with the "user match" suggestion. Evaluating bidirectional preferences involves analyzing mutual compatibility[48].

A study utilized two algorithms to extract prerequisite relations at both concept and course levels. The "GuessUNeed" recommendation approach, based on a neural attention network and course prerequisite relations embeddings, was found to be effective in real-world datasets[63].

A study developed a method for grouping individuals based on preferences and creating course suggestions for businesses using specialized word embeddings, Word2Vec, modified K-means algorithm, and perceptron adversarial learning, generating high-quality results through an opinion-based deep learning algorithm[42].

The system uses employee skill profiles to predict talent representation and demand recognition to identify growth requirements. An enhanced version provides explainable recommendations based on competence representation, addressing missing abilities in profiles[64].

The study [53] introduces a gradient technique for balancing exploration and exploitation in user profiles, employing recurrent context-aware learning for current information and a dynamic baseline method for future preferences, undergoing extensive real-world dataset testing.

*2) Deep Learning Approach*

Deep Learning is gaining popularity in MOOC course RS due to its ability to create tailored suggestions from large data sets, while Neural Networks provide context-aware suggestions. These technologies manage structured and unstructured data sources, enhancing the overall learning experience. The research explored papers utilizing deep learning methodologies, with several techniques being discussed in this summary. The authors in[44] proposed a personalized exercise recommendation system, considering students' learning status and knowledge points. The system improved recommendation precision and diversity, as confirmed by an empirical study.

The study[65] introduces the "Attentional Manhattan Siamese Long Short-Term Memory" (AMSLSTM) network, a self-attention technique that enhances suggestion accuracy by learning students' interests.

A study proposes a custom recommender system for formal learning platforms, using Siamese LSTM networks to assess course descriptions' semantic similarity[33].

The ACKRec approach is a method proposed to improve knowledge in Massive Open Online Courses (MOOCs) by combining a graph convolution network and a heterogeneous information network, incorporating contextual data from multiple meta-paths and using an extended matrix factorization approach[66].

The study[?] proposed "Top-N Personalized Recommendation with Graph Neural Network" (TP-GNN) as a solution for Massive Open Online Courses (MOOCs). The study utilized two aggregate functions to manage the attention mechanism and the neighbors in sequencefor final item representation. Experimental results showed TP-GNN improved performance on a real-world course dataset.

[67] presents a model for a "Heterogeneous Information Ntwork" (HIN) using MOOCs to capture interactions between elements. The model uses an "Attention Collaborative Extended Matrix Factorization" Based Model (ACMF) to provide tailored recommendation services for MOOC courses. It considers four entities: knowledge, instructor, university, and video, and successfully blends explicit and implicit representations.

Existing graph models suffer from decreased performance due to data sparsity issues, biased recommendations, and incorrect contrasting pairings, resulting in graph noise due to a variety of concepts. To solve these issues, [55] Sharma introduces the ROME framework, which uses hyperbolic angular space to create representations of people and concepts based on their interactions. The framework maximizes mutual information between hyperbolic and Euclidean space representations, improving pairwise discriminative power and angular decision margin.

The article[36] presents a novel collaborative filtering recommendation method for art and MOOC resources, utilizing deep learning techniques, metapath context embedding, attention mechanisms, Laplacian matrix integration, and text word vectors to improve prediction accuracy and stability, outperforming other methods.

*3) OtherApproaches*

Many other approaches were deviced during the defined period for which the survey is being conducted. The approaches include Immune algorithm + Mixed concept mapping[68], "C4.5 decision tree + Multilayer perceptron (MLP) neural network + naive Bayes (NB) classifier"[24], association rule mining and a priori algorithms were used and two algorithms, class identification (CI) and subclass Identification(ID) algorithms were devices in [69]. In [49]Hyper edge embedding + Graph neural network + Attention mechanism is used, trust based model in proposed in [70], k- means + data analytic[71], Collaborative Filtering + K-nearest neighbor algorithm + Non-negative Matrix Factorization + Cosine similarity were used in [72], Collaborative filtering + Belief Networks are used in the article [51],[73] used Adam algorithm, some authors used "multi-entity relational Self-symmetric meta-path" (MSMP), "associative relational self-symmetric meta-graph", meta-relationship correlation measure[56], and in [74] authors used HIT algorithm + Collaborative Filtering and the authors in [75]used , RNN, LSTM, N-Gram, and Jaccard similarity.

In addition to course RS, the review examined various approaches for RS [24],[32],[44],[48],[66],[76],[77],[78],[79],[80] implying that these methodologies might considerably enhance research and development in course RS.

### *E. The Problems in the Course RS*

MOOC course RS face the same issues as traditional RS. These issues include the "cold start problem", "data sparsity", "scalability", grey sheep problem, outliers, data overload, and lack of context awareness, among others.

**Data overload:** The overwhelming amount of data in MOOCs, including course information, learners, and interactions, may overburden the recommendation system, complicating suggestions and assessments.

**Lack of Context Awareness:** Contextual information, including user demographics, learning goals, prior knowledge, time constraints, and learning styles, can influence course recommendations and user preferences, causing potential problems.

**Data Sparsity:** Data scarcity in MOOCs can lead to incorrect suggestions due to limited user interactions, narrow interests, and lack of feedback, ratings, and reviews.

**Grey Sheep Problem:** Gray sheep problems arise when users have unique tastes that don't align with others, posing challenges for recommendation systems in understanding their potential needs.

**Cold Start Problem:** The RS faces a challenge in providing suitable recommendations for new users or objects due to limited historical data.

**Outliers:** Outliers, or exceptions, are significant differences in data points from the rest, often caused by errors, input issues, or anomalies, and can significantly impact Collaborative Filtering (CF).

**Scalability:** As MOOCs gain popularity, a recommendation system's ability to handle growing data on users and courses may be compromised, potentially affecting customer satisfaction and participation.

### *F. Evaluation in Course RS*

The authors used various evaluation metrics to assess the performance of RS, including precision, recall, F1-measure, MAE, RMSE, MRR, and NDCG. These metrics provided crucial information on the precision, comprehensiveness, rate of error, rank quality, and overall efficacy of the recommendation algorithms used in the study. They thoroughly investigated and compared the performance of various course selection algorithms in various areas.

**Precision@N:**

In MOOCs Course RS Precision refers to the number of relevant courses recommended to users in relation to the overall number of courses accessible with MOOCs.

$$Percision@N = \frac{(No.of RelvantCoursesinTopN)}{(TotalNo.of Courses)} \quad (1)$$

Here N is the number of recommendations made to the user.

**Recall@N:**

The evaluation of recommended items, specifically the proportion of acceptable courses in the MOOC course recommendation system, is crucial in ensuring user satisfaction and satisfaction.

$$Recall@N = \frac{(No.ofRelvantCoursesinTopN)}{N} \quad (2)$$

Here N is the number of recommendations made to the user.

**F1-Score@N:**

The F1-score, a metric that blends recall and precision, is used to assess the effectiveness of a recommendation system, providing a holistic assessment of recommendation quality in MOOC course RS.

$$F1 - Score@N = \frac{(2 \times Precision@N \times Recall@N)}{(Precision@N + Recall@N)} \quad (3)$$

**Mean Reciprocal Rank (MRR):**

The mean reciprocal ranking (MRR) is a tool used to calculate the ranking performance of the first suitable item suggested to a user, highlighting the system's ability to place relevant courses at the top of the recommended list.

$$MRR@N = \frac{1}{S}\sum_{i=1}^{s}\frac{1}{Rank_i} \quad (4)$$

Here S represents the total number of users or queries in the evaluated dataset

$Rank_i$ signifies the position of the initial relevant Course recommended to the user within the top-N outcomes.

**Normalized Discounted Cumulative Gain (NDCG):**

The metric assesses the effectiveness of ranking relevant items in a suggestion list, considering both the relevance and ranking position of recommended products, with higher-ranked items receiving higher ratings.

$$NDCG@N = \frac{(DCG@N)}{(IDCG@N)} \quad (5)$$

Here discounted cumulative gain (DCG@N) is given as

$$DCG@N = \sum_{i=1}^{n}\frac{Relv_1}{log_2(i+1)} \quad (6)$$

And Ideal Discounted Cumulative Gain (IDCG@N) ranking of top N recommendations represents DCG@N rankings in descending order.

$$DCG@N = \frac{Relv_{i1}}{log_2(i+1)} + \frac{Relv_{i2}}{log_2(i+1)} + ... + \frac{Relv_{in}}{log_2(i+1)} \quad (7)$$

Here $i_1$, $i_2$,......., $i_n$ are the rankings in descending order.

**Mean Absolute Error (MAE):**

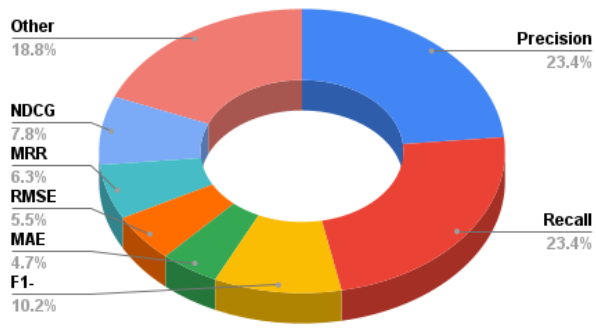


Figure 12. Distribution of the Various Assessment Metrics used by the Authors

MAE is a measure of the average difference between projected and actual user ratings, indicating the accuracy of a recommendation system in predicting user preferences, particularly in MOOC course RS.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (8)$$

Where $y_i$ is is the actual output value, $\hat{y}_i$ is the predicted output value and N is the number of recommendations

**Root Mean Square Error (RMSE):**

RMSE is a mathematical concept that measures the error or variance between expected and actual ratings, with higher numbers indicating larger faults. It is used to measure the accuracy of the system's predictions in MOOC course RS.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(|y_i - \hat{y}_i|)^2}{N}} \quad (9)$$

Where $y_i$ is the actual output value, $\hat{y}_i$ is the predicted output value and N is the number of recommendations.

The pie chart in Figure 12 illustrates the distribution of assessment metrics used by publications to evaluate built system performance, including accuracy, recall, F1-measure, MAE, RMSE, MRR, and NDCG, illustrating the relative use of these measures. The pie chart shows the frequency of publications using specific assessment measures, with precision and recall being the most commonly used. The NDCG metric is also gaining popularity in evaluating RS performance. This visualization helps researchers and professionals understand the assessment landscape and identify trends, patterns, and areas of attention in the MOOC course RS study domain.

TABLE VII. DISTRIBUTION OF THE ARTICLES BASED ON THE APPROACHED USED

| Approach | Method | Articles |
|---|---|---|
| Machine Learning | Collaborative filtering | X. Jing and J. Tang[31], L. Wu[36], H. Zhang et al.[51], J. Gong et al[66], C. Wang et al.[64], V. Garg and R. Tiwari[81], H. Jain and Anika[60], J. Wang et al.[82], K. Dai et al.[83], X. Yang and W. Jiang[74], Y. Pang et al.[84] |
| | Dirichlet distribution algorithm | S. Yin et al.[7] |
| | Non-negative matrix factorization (NMF) | R. Campos et al.[30], R. Campos et al.[46] |
| | AI/ML algorithms | I. Palomares[48] |
| | Random forest | Z. Zhao et al[63] |
| | TF-IDF | Y. Xue[42], B. Mbipom et al.[85] |
| | Perceptron adversarial learning algorithm | Y. Xue[42] |
| | Hybrid filtering | Y. Xue[42], R. Campos et al.[86], F. Liu et al.[87] |
| | Case based method | F. Bousbahi and H. Chorfi[34] |
| | C4.5 decision tree | F. Gasparetti et al.[24] |
| | Matrix factorization | L. Wu[36], X. Wang[49], D. Sheng, J et al.[67] |
| | Latent Dirichlet Allocation | M. Nilashi et al.[61], X. Jiang et al[88] |
| | Knowledge Graphs | H. Zhang et al.[54], H. Jung et al.[89] |
| | Backpropagation algorithm | H. Zhang et al.[90] |
| | Jaccard's Similarity | H.-H. Wang et al.[91] |
| | Content Based filtering | A. A. Neamah et al.[50], R. Huang and R. Lu et al.[92] |
| | Trust Management Mystem (TMS) | K. Elghomary et al.[70] |
| | Multilayer Perceptron (MLP) | S. Sakboonyarat et al.[62] |
| | Back Propagation Gradient Descent | J. Tan et al.[65] |
| | K- means | Y. Xue[42], Y. Li and H. Li[93], B. Mondal et al.[72], H. Aoulad Ali et al.[71] |
| | Knowledge map | Y.-H. Chen et al.[76] |
| | Reinforcement learning | Y. Lin et al.[52], Y. Lin et al.[53], A.-C. Chuang et al.[77] |
| | Clustering and ML algorithms | A. Cohen et al.[57], S. Ardchir et al.[94] |
| | Concept Based filtering | B. Mbipom [95] |
| | Ontology-Based modeling | K. Dai et al.[83], M. Amane et al.[96], H. Sebbaq et al.[97] |
| | Adam algorithm | Y. Zhao et al.[98] |
| | Logistic Regression | M. Dong, R et al.[99] |
| | Association Rule Mining | T. S. Ibrahim et al.[69], H. Zhang et al.[100], J. Xiao et al.[101] |
| | Multi-layer Bucketing | Y. Pang et al.[35] |
| | Map-Reduce | L. Wu [36] |

| Approach | Method | Articles |
|---|---|---|
| Deep Learning | Weighted Knowledge Graph (WKG-r) | P. Lv et al.[44] |
| | Siamese LSTM networks | K. Mrhar et al.[33] |
| | Attentional heterogeneous graph convolutional deep knowledge recommender (AckRec) | J. Gong et al.[66] |
| | Convolutional Neural Networks | L. Wu J.[36], Wang et al.[?], Y. Xue [42] |
| | Graph Neural Networks | X. Wang et al.[49], H. Luo et al.[55] |
| | Graph Convolutional Network | D. Sheng [67] |
| | Attention Mechanism | Y. Lin et al.[52] |
| | "Manhattan Siamese Long Short Term Memory (AMSLSTM) Network" | J. Tan et al. [65] |
| | "Attention-Based Convolutional Neural Networks" | J. Wang et al.[82] |
| | "Recurrent Neural Networks" | S. Pandey et al.[78], N. Roopak et al.[75] |
| | "Siamese Neural Networks" | A. Faroughi et al.[102] |
| | Deep belief Networks | H. Zhang et al.[51] |
| | Attention Networks | Y. Liu et al.[103] |
| | Deep Reinforcement learning | J.-W. Tzeng et al.[104] |
| Other Approaches | Javascripts, Nodejs | Z. A. Pardos et al.[32] |
| | Retrieval algorithm | F. Bousbahi et al.[34] |
| | Immune algorithm | S. Wan et al.[68] |
| | Correspondence Analysis | M. Furukawa et al.[105] |
| | Tree structures | Y. Hou et al.[45] |
| | Lingo algorithm | K. M. Alzahrani et al.[47] |
| | Stc algorithm | K. M. Alzahrani et al.[47] |
| | Analyzing infix Suggesters algorithm | K. M. Alzahrani et al.[47] |
| | Similarity Matrix | S. Prabhakar et al.[106] |
| | Hawkes Process | Y. Pang et al.[107]] |
| | "Multi-entity relational Self-symmetric Meta-Path (MSMP)" | P. Hao et al.[56] |
| | HITS Algorithms | X. Yang et al.[74] |

## 4. Conclusions and Future Work

Research on integrating Course Recommendations in Massive Open Online Courses (MOOCs) has shown potential to enhance students' learning experiences. Until 2016, academics focused on implementing course, peer, and thread CR using Collaborative Filtering (CF), Content-Based Filtering (CBF), and Hybrid approaches. In 2017, there was a shift towards using Recommendation Systems (RS) in MOOCs, incorporating advanced techniques like neural networks, deep learning, and data mining. During the Covid-19 pandemic, there was a surge in articles focusing on RS, indicating a shift towards personalized learning experiences. Scholars initially used learner profiles and course features, but since 2017, there has been a rise in using student activities and learning types for RS design. Hybrid systems have also gained popularity in Course RS. However, the lack of a consistent dataset, primarily from the computer science discipline, makes benchmarking difficult. A complete dataset is needed for recommender systems to evaluate algorithms and assess results.

The design of recommender systems (RS) in MOOCs has been under debated, with datasets primarily focusing on extended MOOCs. Researchers have overlooked scalability and temporal complexity, and the use of NDCG for ranking recommendations. MOOCs provide student profiles, behavioral patterns, and course information, which could be explored through a comprehensive comparison study. RS aim to suggest courses based on students' interests, skills, and market demand. Quantitative and qualitative assessments, such as surveys, interviews, and questionnaires, are needed to evaluate the precision and quality of these recommendations.

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