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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 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 include 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. The literature study examines cutting-edge course Recommendation System in depth, examining recent developments, difficulties, and future work in this field.

Keywords: MOOCs, Course RS, Machine Learning, Deep Learning, Recommendation Systems(RS)

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

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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].

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.

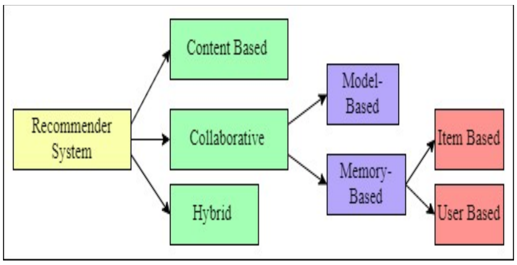

Figure 1. Classification of the Recommender System

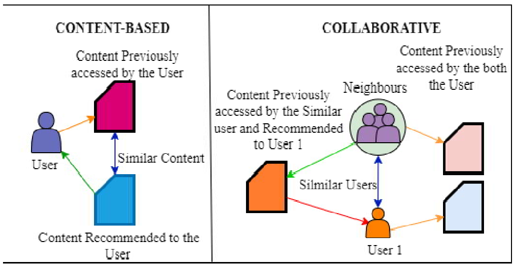

Figure 2. Content-Based & Collaborative RS

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 anticipated rating is determined by the degree of similarity between an item and its neighbors, with a higher level of similarity leading to 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].

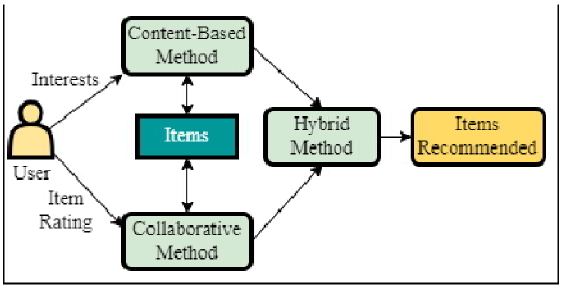

Figure 3. Hybrid RS

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.

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[37]. 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[39].Figure 4 provides a more comprehensive view.

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)[40], 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.

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

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

The search phrase is optimized for title, abstract, and keywords, with adjustments made to meet the specific requirements of each database on individual sites[41]. 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.[41]. Papers only in the English language are considered

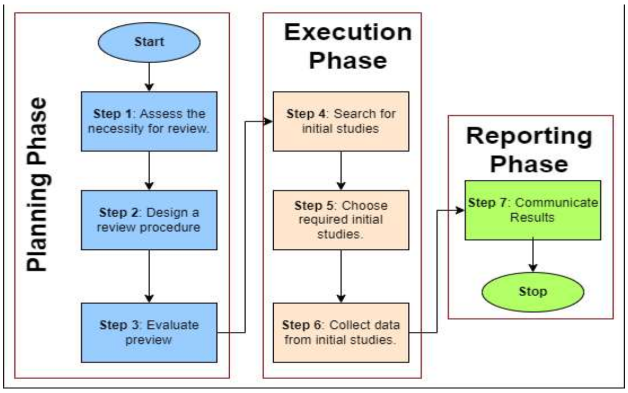

Figure 4. Systematic Literature Review (Okoli and Schabram, n.d.)

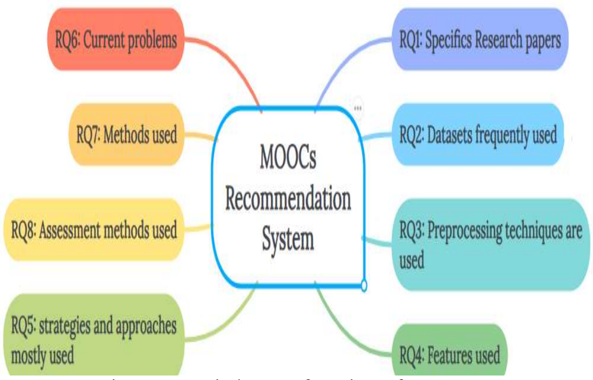

Figure 5. Mind Map of Review of MOOCs RS

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. The keywords are used to find relevant published works from designated sources, while the timeframe refers to the exact period of articles' publication.

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

TABLE II. RESEARCH QUESTION AND MOTIVATION

ID	Research Question	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

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.

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.

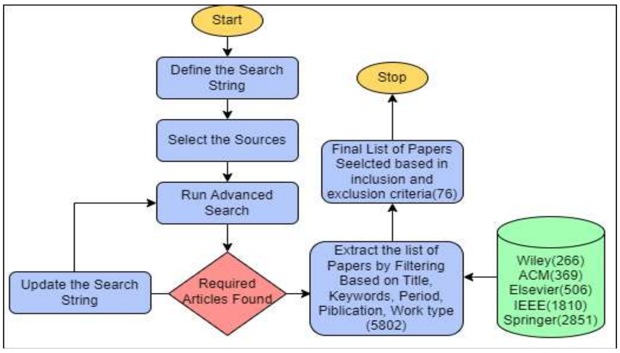

Figure 6. Search and Selection Mechanism

The study selected 76 papers for further review based on Table III's inclusion and exclusion criteria[42].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.

TABLE III. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	• Articles published in Journals and conferences of high impact • Articles that have a well-defined motive, methodology, experimentation and results • Articles which are relevant to the MOOCs Course RS • Articles Published in the duration of 2015-2023
Exclusion Criteria	• Research that excludes experimental outcomes and relies on unclear datasets • Studies that go beyond MOOC RS's Scope • Research papers written in languages other than English • Unpublished studies • Review or survey articles

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

We have researched a variety of scholarly sources.Specifically, we examined content from 7 book sections, 36 conferences, and 33 scholarly journals.

The study collected diverse viewpoints and ideas from academic literature, providing a comprehensive understanding of the course RS in MOOC context. The review used 9% Springer book chapters, 44% various journal publications, and 47% conference proceedings, with a significant percentage of articles from Springer, various journals, and conference proceedings.

TABLE V. NUMBER OF ARTICLES PUBLISHED FROM 2015-2023

Publisher	Year							
	2016	2017	2018	2019	2020	2021	2022	2023
ScienceDirect	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

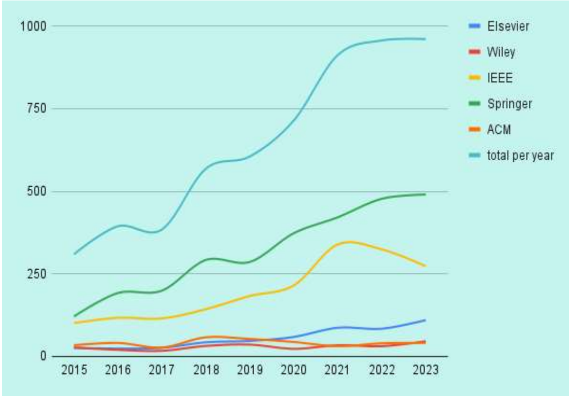

Figure 7. Publications in Journals and Conferences

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.

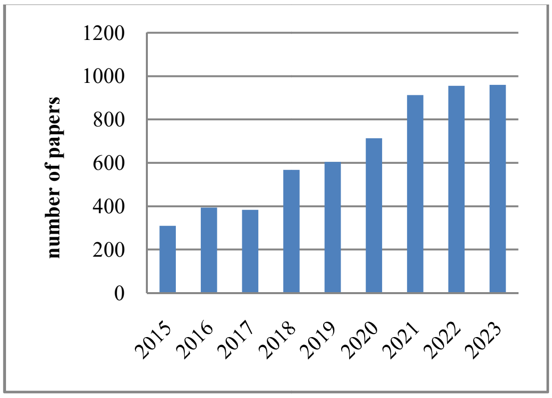

Figure 8. Total Papers published per year

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.

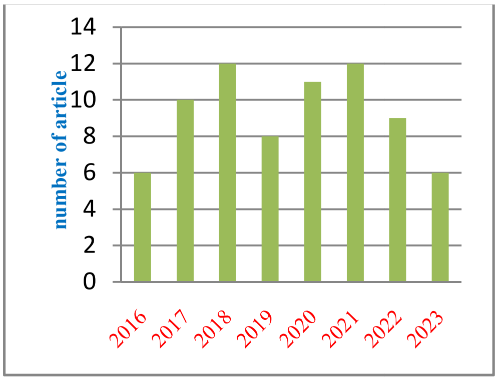

Figure 9. Total Papers published per year

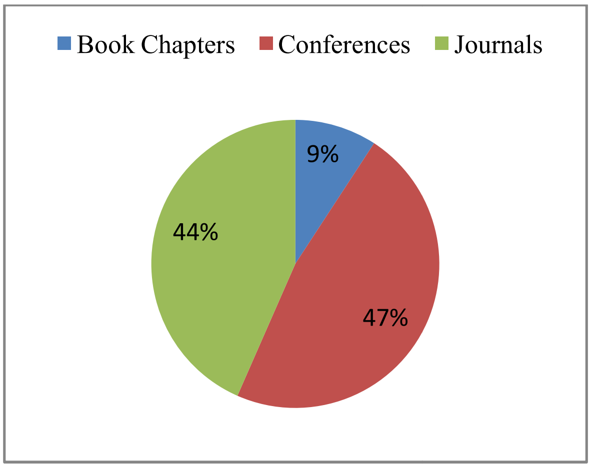

Figure 10. Distribution of type of Papers

The other data set like Facebook[43], "European Expert Network on Economics of Education (EENEE")[44], "Network of Experts on Social Aspects of Education and Training(NESET)"[44], Canvas[34], Classroom data[45], university data[46], iCourse[7],[47], Khan Academy[30],[48],[49], kaggle[50], Udacity[24],[49], MovieLens[51],[52],[53], MOOCCourse[54], [55], MOOCCube[54],[55],[56],[57],[58], Coursetalk[35],[59]are to name a few that were used in 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[60].

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.

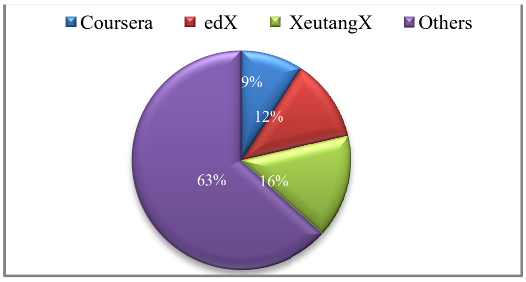

Figure 11. Distribution of Datasets Used in Articles

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[61]. 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.

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

D. Approach techniques

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

1) Machine Learning Approach

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

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

Approach	Method	Articles
Machine Learning	Collaborative filtering	[31],[36],[53],[62],[63],[64],[65],[66],[67],[68],[69]
	Dirichlet distribution algorithm,	[7]
	Non-negative matrix factorization (nmf)	[30],[48]
	AI/ML algorithms	[50]
	Random forest	[70]
	TF-IDF	[44],[71]
	Perceptron adversarial learning algorithm	[44]
	Hybrid filtering	[44],[72],[73]
	Case based method	[34]
	C4.5 decision tree	[24]
	Matrix factorization	[36],[51],[74]
	Latent Dirichlet Allocation	[75],[76]
	Knowledge Graphs	[56],[77]
	Backpropagation algorithm	[78]
	Jaccard's Similarity	[79]
	Content Based filtering	[52],[80]
	Trust Management Mystem (TMS)	[81]
	Multilayer Perceptron (MLP)	[82]
	Back Propagation Gradient Descent	[83]
	K- means	[44],[84] [85],[86]
	Knowledge map	[87]
	Reinforcement learning	[54],[55],[88]
	Clustering and ML algorithms	[59],[89]
	Concept Based filtering	[90]
	Ontology-Based modeling	[67],[91],[92]
	Adam algorithm	[93]
	Logistic Regression	[94]
	Association Rule Mining	[95],[96],[97]
	Multi-layer Bucketing	[35]
	Map-Reduce	[36]
Deep Learning	Weighted Knowledge Graph (WKG-r)	[46]
	Siamese LSTM networks	[33]
	Attentional heterogeneous graph convolutional deep knowledge recommender (AckRec)	[62]
	Convolutional Neural Networks	[36],[37],[44]
	Graph Neural Networks	[51],[57]
	Graph Convolutional Network	[74]
	Attention Mechanism	[54]
	"Manhattan Siamese Long Short Term Memory (AMSLSTM) Network"	[83]
	"Attention-Based Convolutional Neural Networks"	[66]
	"Recurrent Neural Networks"	[98],[99]
	"Siamese Neural Networks"	[100]
	Deep belief Networks	[53]
	Attention Networks	[101]
	Deep Reinforcement learning	[102]
Other Approaches	Javascripts, Nodejs	[32]
	Retrival algorithm	[34]
	Immune algorithm	[103]
	Correspondence Analysis	[104]
	Tree structures	[47]
	Lingo algorithm	[49]
	Stc algorithm	[49]
	Analyzing infix Suggesters algorithm	[49]
	Similarity Matrix	[105]
	Hawkes Process	[106]
	"Multi-entity relational Self-symmetric Meta-Path (MSMP)"	[58]
	HITS Algorithms	[68]

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[43] 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[65] 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[75],[82], Researchers have developed a recommendation model for Massive Open Online Courses (MOOCs) that uses Deep Learning and a Multilayer Perceptron 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[50].

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[70].

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[44].

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[63].

The study [55] 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 Approaches

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[46] 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[83] 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[62].

The study[37] 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 sequence neighbors and an attention mechanism for final item representation. Experimental results showed TP-GNN improved performance on a real-world course dataset.

[74] presents a model for a heterogeneous information network (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, [57] 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) Other Approaches

Many other approaches were deviced during the defined period for which the survey is being conducted. The approaches include Immune algorithm + Mixed concept mapping[103], 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 [95]. In [51]Hyper edge embedding + Graph neural network + Attention mechanism is used, trust based model in proposed in [81], k- means + data analytic[86], Collaborative Filtering + K-nearest neighbor algorithm + Non-negative Matrix Factorization + Cosine similarity were used in [85], Collaborative filtering + Belief Networks are used in the article [53],[107] used Adam algorithm, some authors used multi-entity relational Self-symmetric meta-path (MSMP), associative relational self-symmetric meta-graph, meta-relationship correlation measure[58], and in [68] authors used HIT algorithm + Collaborative Filtering and the authors in [99]used , RNN, LSTM, N-Gram, and Jaccard similarity.

In addition to course RS, the review examined various approaches for RS [24], [32], [46], [50], [62], [87], [88], [98], [108], 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.

$$\text{Percision@N} = \frac{\text{No. of Relvant Courses in top N}}{\text{Total No. of Courses}}$$

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

$$\text{Recall@N} = \frac{\text{No. of Relvant Courses in top N}}{\text{N}}$$

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

$$\text{F1} - \text{Score@N} = \frac{2 \times \text{Percision@N} \times \text{Recall@N}}{\text{Percision@N} + \text{Recall@N}}$$

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.

$$\text{MRR@N} = \frac{1}{S}\sum_{i=1}^{S}\frac{1}{\text{Rank}_i}$$

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 user u 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.

$$\text{NDCG@N} = \frac{\text{DCG@N}}{\text{IDCG@N}}$$

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

$$\text{DCG@N} = \sum_{i=1}^{N}\frac{\text{Relv}_i}{\log_2(i+1)}$$

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

$$\text{IDCG@N} = \frac{\text{Relv}_{i1}}{\log_2(i+1)} + \frac{\text{Relv}_{i2}}{\log_2(i+1)} + \cdots + \frac{\text{Relv}_{in}}{\log_2(i+1)}$$

Here i1, i2,……., in are the rankings in descending order.

Mean Absolute Error (MAE):

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.

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

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.

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

Where y_i is is the actual output value, $\hat{y}_i$ is the predicte 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.

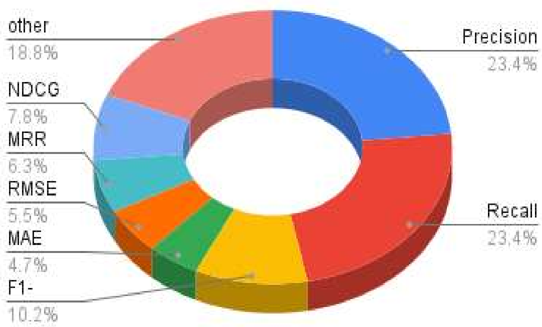

Figure 12. Distribution of the various assessment metrics used by the authors

4. CONCLUSION AND DISCUSSION

Research on integrating Course Regression (CR) in Massive Open Online Courses (MOOCs) has shown potential to boost their popularity and enhance students' learning experiences. Until 2016, academics primarily focused on implementing course, peer, and thread CR using Collaborative Filtering (CF), Content-Based Filtering (CBF), and Hybrid approaches[109]. In 2017, there was a shift towards using Learning Resources (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.

A Recommendation System (RS) for MOOCs is being increasingly developed using machine learning and neural networks to generate suggestions based on various user traits and behaviors. This trend is driven by the need to generate suggestions based on a wide range of user behaviors. However, the lack of a consistent dataset, primarily from the computer science discipline, makes benchmarking difficult, and researchers are using different datasets to evaluate their RS. The current MOOC dataset[110] based on ratings, only includes course teacher and rating data. A complete dataset is needed for recommender systems to evaluate algorithms and assess results. Specialist data management solutions are needed, as most research uses publicly available datasets from platforms like Coursera, edX, and XuetangX.

The design of recommender systems (RS) has not been adequately addressed or debated, with datasets mainly catering to extended MOOCs (xMOOCs). Researchers have overlooked scalability and temporal complexity, and the use of NDCG (Normalized Discounted Cumulative Gain) to assess recommendation list ranks. MOOCs provide student profiles, behavioral patterns, and course information, which could be explored through a comprehensive comparison study to assess the importance of various learner and course characteristics in the recommendation evaluation process.

MOOC course Recommendation Systems (RS) aim to suggest courses based on students' interests, skills, and market demand. To evaluate the precision and quality of these recommendations, both quantitative and qualitative assessments should be conducted. Surveys, interviews, and questionnaires can be used to gather feedback from students, teachers, and providers. More research is needed to establish precise techniques for assessing RS in MOOCs.

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