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Review Article

A Machine Learning Based Approach to Course and Career Recommendation System: A Systematic Literature Review

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Abstract: Learners are continually faced with choosing appropriate courses or making career choices due to increased educational opportunities. The emergence of machine learning-based course and career recommender systems has the potential to address this issue, offering personalized course recommendations tailored to individual learning pathways, preferences, and learning history. The optimization and feature engineering techniques and practical deployment environments have not been collectively examined in the previous research, despite the significant advancements in this area of research. Furthermore, previous research has rarely synthesized how these technical components help students choose appropriate courses and careers. This systematic review was carried out to investigate the current state of machine learning-based course and career recommender systems, focusing on key elements, such as primary data sources, feature engineering methods, algorithms, optimization techniques, evaluation metrics, and the environments where the existing course recommendation models are deployed. The PRISMA method for conducting a systematic review was used to choose studies that met the requirements for inclusion and exclusion. The study findings show significant reliance on interpretable and traditional machine learning algorithms, such as K-Nearest Neighbor and Random Forest, to develop recommender models. Feature engineering remains basic, as most studies rely on normalization, while optimization processes are often underreported. Also, evaluation metrics varied widely, impeding comparability, while most of the recommender models are deployed in an e-learning environment, leaving the traditional learning environment underrepresented. Furthermore, the study findings identified issues including data sparsity and diversity, data security and privacy, and changes in learner preferences that may have an impact on the performance of recommender systems while recommending further studies to make use of standardized optimization methods, and automated domain-informed feature engineering frameworks, benchmark and annotated datasets in developing models the gives priority to learners' success and educational relevance.

Keywords: Artificial Intelligence; Course Recommendation System; Deep Learning; Machine Learning; Recommender System; Systematic Review.

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1. Introduction

Personalized learning is increasingly recognized as an important aspect of modern education, allowing educational experiences to be channeled to the learning styles, needs, and preferences of individual students, solving their problem of cognitive overload [1], [2]. A personalized learning recommendation system can analyze the data produced by users to predict their preferred knowledge and, hence, recommend the information they are interested in [3]. Recommender systems play a vital role in personalized education because they provide students with suggestions for careers, courses, and learning paths that align with their needs and academic goals [4]. The number of courses in the framework of smart education today has dramatically increased. Thus, the corresponding course selection issue plays a significant role in modern education [5]. Generally, recommendation systems are generated based on user preferences, item characteristics, user-item interaction history, and additional information, such as time or space, to find items of interest to users and make personalized recommendations [6]. Career Recommender Systems and course recommender systems perform complementary roles in the educational field. A course recommender system is designed to suggest learning modules or academic subjects that align with students' interests and academic paths [2]. At the same time, career recommendation primarily aims to guide learners toward a long-term professional trajectory by analyzing their skills, performance, goals, and personality traits, which will help learners become aware of the career tracks suitable for them [7]. Despite their distinctions, both systems need to be studied simultaneously because course selection directly impacts career orientation, as the job profile chosen by a student is linked to the learning path with career goals [8], [9]. A poorly guided course recommendation may limit a student's career prospects, while excellent career guidance can inform more deliberate and accurate course selection. Therefore, understanding both systems guarantees personalized and cohesive academic-to-career pathways, enhancing overall educational outcomes.

In contrast to recommendations in other domains like movies, tourism, and music, where user preferences are usually subjective, short-term, and derived from simple interaction data like user clicks or ratings [10], course recommendations address more complex and impactful features like prerequisite knowledge, students' ambitions, curriculum structure, and extended learning histories which elevate their complexities and importance above those in other industries [11]. It is important to note that the knowledge points between courses are closely related, displaying a strong sequential relationship. For example, one of the prerequisites for a course in Computer Engineering is knowledge of mathematics, as it will not be easy to understand the content of a course in Computer Engineering without first understanding the rudiments of Mathematics. Initially, these systems were built using traditional methods such as rule-based logic or content-based filtering, which, while useful, had limitations in handling the growing complexity and diversity of educational data. As educational environments became more intricate, the need for advanced methods became apparent, leading to the integration of machine learning techniques. Literature has shown that existing research in course or career recommender systems primarily focuses on traditional recommendation techniques, like content-based filtering, collaborative filtering, and hybrid methods. Though traditional approaches have laid the foundation for developing recommender systems, they suffer from challenges of data sparsity, the cold start problem, and scalability issues [2], [10], [11], [12], [13]. Researchers are developing more efficient and effective machine-learning recommendation models to address these challenges and increase accuracy and user satisfaction [14]. Introducing machine learning and deep learning models into course recommendations has brought great innovations in educational recommender systems. This transformation enables more dynamic, accurate, and scalable models, which is critical for supporting personalized learning at scale. Adopting machine learning in course recommendation systems has opened up new possibilities for enhancing educational outcomes. Machine learning-based algorithms, including matrix factorization, supervised and unsupervised machine learning, and deep learning, can handle large and complex datasets, adapt to changing user preferences, and provide more personalized and accurate recommendations [15].

Cold start and data sparsity, scalability, and privacy are the common challenges faced by traditional recommender techniques like content-based and collaborative filtering [10]. The performance of recommender systems can be improved significantly by adopting model-based machine learning algorithms like KNN, Random Forest, SVM, Naïve Bayes, Deep learning, and transformer models, which can learn complex data patterns and improve recommendation accuracy and personalization. Despite the growing body of research on model-based machine learning algorithms in developing course and career recommendation systems, several challenges and gaps persist in the literature, necessitating this systematic review. First, previous studies could not examine the educational environments where course recommendation systems are mostly deployed. Also, the previous reviews have not adequately examined feature engineering and optimization techniques despite their importance in improving models' accuracy. The identified gaps underscore the need for an in-depth review that addresses real-world implementation challenges and algorithmic trends, thereby driving future research toward more robust recommender models. It is important to note that researchers and policymakers in the educational sector may not be cognizant of the limitations, capabilities, and best practices associated with these models. By systematically reviewing the various machine learning approaches used in course recommendations, this review aims to provide a clearer understanding of the state of the art, highlight the weaknesses of different methods, and offer a roadmap for ensuring that the potential of machine learning is fully realized in enhancing personalized learning experiences. The specific contributions, outlined as objectives in Section 2 and guided by the research questions in Section 3.1, set this review apart from existing literature by offering a more comprehensive and deployment-aware perspective.

2. Review of Related Works

To support personalized course and career guidance, many systematic reviews have provided critical insights into algorithmic trends and implementation challenges regarding the role of machine learning in educational recommender systems. For instance, [16] reviewed machine learning-based recommendation systems for e-learning. The review categorized recommender systems based on collaborative filtering, content-based, knowledge-based, and hybrid systems while analyzing the datasets, machine learning models, and evaluation metrics. Scalability and learners' interaction with the learner management systems were the identified challenges of recommender systems. In another study, [17] carried out a systematic literature review on the research trends in recommender systems for e-learning to identify the correlations between the recommender models and e-learning platforms. The research findings show that most reviewed studies integrated adaptive mechanisms in their e-learning systems, which dynamically adjust recommendations according to user behavior and preferences. The review of [18] on Deep Learning E-Learning Recommendation Systems identifies cold start, data sparsity, scalability, and privacy as the major challenges in recommender systems. Similarly, the review of [19] analyzed and classified existing recommendation systems in social and e-learning environments. The findings of their research show that most studies pay little attention to social learning. Also, smaller datasets and cold start were the major challenges of course recommender systems. The systematic review of [11] on recommender systems in e-learning environments focused on deep learning models while neglecting other model-based machine learning algorithms. The study of [20] examined how learning is measured and optimized using educational recommender systems. Their review focuses only on evaluation and performance metrics. Also, the systematic review of [21] on machine learning approaches in course recommender systems focused primarily on recommendations for e-learning platforms like MOOCs while neglecting traditional or blended classrooms, which could limit the generalizability of their research findings.

The primary objective of this systematic review is to thoroughly examine and analyze the different machine-learning approaches used in course recommendation systems, focusing on studies published between 2017 and 2024. This time frame is chosen to ensure that the review includes the most recent and relevant advancements in machine learning and recommendation systems while capturing significant earlier developments that laid the foundation for current practices. Specifically, this systematic literature review contributes to knowledge in the following ways:

- Identification of data sources in course recommender systems;
- Examines machine learning algorithms often utilized in developing or implementing course recommender systems.
- Investigate the various feature engineering approaches applied in a course recommender model.
- Explore the optimization techniques for developing machine learning recommender models for course selection.
- Examine the evaluation metrics used for assessing the performance of machine learning-based course recommender systems.
- Investigate the various educational environments where various recommender systems are deployed.

The remainder of the study is organized as follows: Section 2 presents the methodology employed in the systematic review, detailing research questions, search strategy, inclusion and exclusion criteria, articles selection process, and quality assessment, as well as the data extracted from the selected articles. Section 3 presents a meta-analysis of data extracted from selected studies, addressing the research questions established in Section 2.1 to guide the study. Section 4 discusses the study findings based on the research questions. Section 5 highlights the identified challenges from the systematic literature review with their corresponding future research directions for researchers to explore. Finally, Section 6 provides the overall summary and conclusion of the study.

3. Methodology

This section presents the systematic literature review method used in the research. A systematic literature review procedure used by [22] was adopted for research reporting to achieve the study objectives, as shown in Figure 1. The method comprises problem identification, screening, eligibility, inclusion and exclusion criteria to ensure relevance and quality, and data extraction and synthesis. Each research methodology component helps understand the machine learning algorithms deployed in building course recommender systems, focusing on data sources, feature engineering methods, machine learning models considered, optimization techniques adopted, evaluation metrics, and educational settings deployed. By following these steps systematically, the review aims to present a well-structured analysis that provides valuable insights for researchers and practitioners alike.

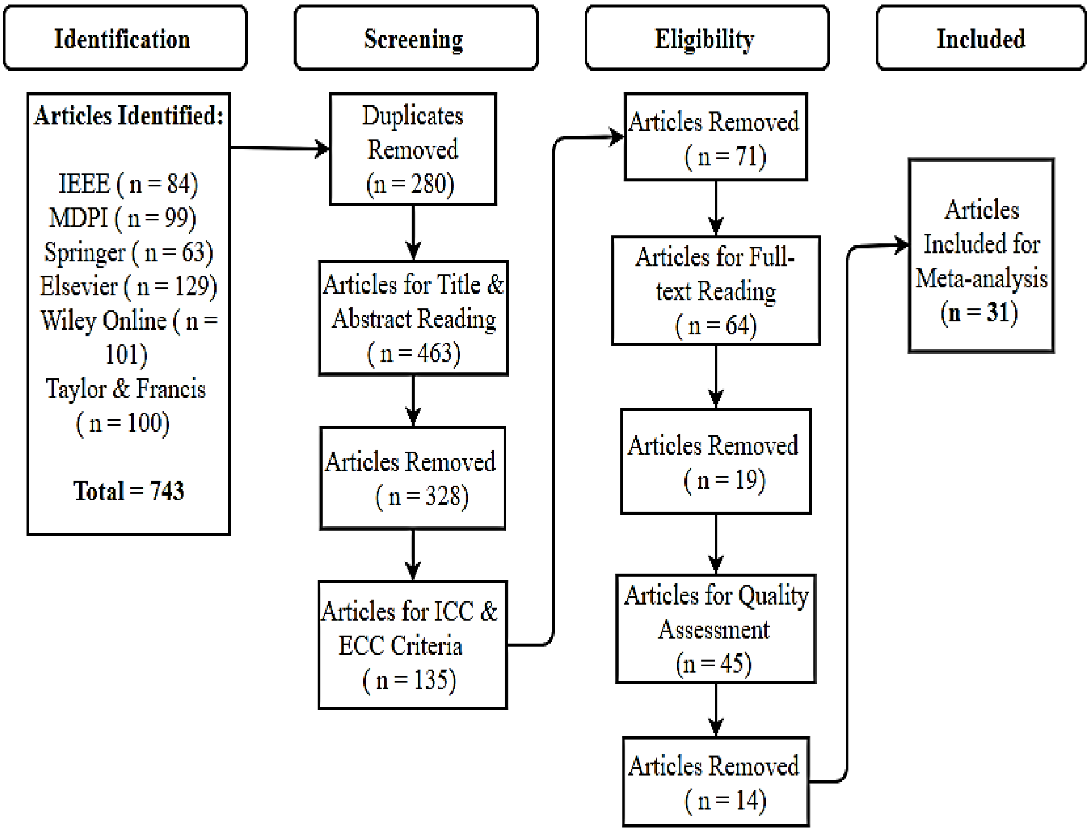

Figure 1. PRISMA Structure for Systematic Review

3.1. Research Questions

1. What are the primary data sources for developing machine learning course recommendation systems?
2. What feature engineering methods have been applied in course recommender models?
3. What machine learning algorithms are primarily adopted in course recommender systems?
4. What optimization techniques are commonly used to enhance the performance of machine learning models in course recommender systems?
5. What evaluation metrics are commonly used to measure the performance of machine learning-based course recommender systems?
6. In which educational settings are machine learning-based course recommender systems most commonly deployed?

3.2. Search Strategy

The search strategy was used to find important and related literature across databases like IEEE Xplore, Science Direct, Taylor and Francis, MDPI, Springer, and Google Scholar, which house extensive research on recommender systems, machine learning, Artificial Intelligence, and deep learning. To guarantee the inclusion of all relevant studies, a combination of related keywords and search terms was employed to capture a broad range of studies. These include terms or phrases like "Recommender systems", "Recommendation system", "machine learning", "deep learning", "e-learning", "artificial intelligence", "course recommender system", "career recommender system", as well as "deep learning methods in course recommendation". These keywords were selected to cover a wide area of research involving algorithmic techniques for recommending educational content. While "deep learning" and "machine learning" concentrate on studies that employ model-based algorithms, "course recommender system" and "career recommender system" restrict the focus to the educational field. Also, to combine search queries effectively to guarantee precision and comprehensiveness, the Boolean operators (AND, OR) were used. For example, combinations such as ("Course Recommender System" OR "Career Recommender System") AND ("Deep Learning" OR "Machine Learning") were used to find papers that particularly use learning algorithms for education-related recommendation tasks.

3.2. Inclusion and Exclusion Criteria

Table 1 shows the details of the inclusion and exclusion criteria

Table 1. Inclusion and Exclusion Criteria.

Code	Inclusion Criteria (IC)
IC1	Articles published between 2017 to 2024
IC2	Studies that focused on model-based machine learning course recommender systems.
IC3	Articles published either in a journal or conference proceedings
IC4	Research papers that show well-defined methods and evaluations
IC5	Open-access studies
Code	**Exclusion Criteria (EC)**
EC1	Studies not related to machine learning course recommender systems.
EC2	Studies that use only traditional recommendation techniques
EC3	The article should not be an abstract only.
EC4	Articles written in a language other than English
EC5	Studies that score below 60% threshold Quality assessment criteria.

3.4. Selection of Primary Studies

The screening aims to identify relevant articles on course recommender systems that utilize machine learning techniques. The study selection process for this systematic literature review involved three key stages: initial screening, eligibility assessment, and final inclusion. Initially, we identified 743 relevant studies from academic databases such as IEEE Xplore, Wiley Online Library, Science Direct, Taylor and Francis, MDPI, Springer, and Google Scholar, using search terms like "machine learning," "Deep learning," and " course recommender systems." Thus, duplicated articles were tracked and removed following the initial results, leaving 463 articles. During the title and abstract review, studies not directly related to machine learning in course recommendation systems were excluded, and 135 studies were identified as related. In the eligibility stage, IC/EC returned 64 articles; full-text articles were reviewed, and 45 papers were identified to have focused on machine-learning techniques applied to course recommendation systems, used empirical data, and provided insights into model performance and optimization. Multiple researchers reviewed the 45 remaining studies to confirm their validity and quality, after which 31 studies were selected for inclusion in the systematic review. Figure 1 earlier showed the included studies using the PRISMA screening process, while Table 2 shows the 31 selected studies distributed across databases.

The search strategy was used to find very important and related literature across databases like IEEE Xplore, Science Direct, Taylor and Francis, MDPI, Springer, and Google

Scholar, which house extensive research on recommender systems, machine learning, Artificial Intelligence, and

Table 2. Screening stages and studies selected across Databases.

Databases	Initial Query	Duplicate Removal	Title & Abstract	IC & EC Outcome	Full-text Reading	Quality Assessment	Percentage (%)
IEEE	212	154	37	21	18	13	41.94
Science Direct	165	90	50	5	4	4	12.90
Springer	120	73	15	11	9	6	19.35
MPDI	89	65	23	8	3	3	9.68
Google Scholar	75	54	17	9	6	3	9.68
Taylor & Francis	39	15	9	6	3	1	3.23
Willey Online Libary	43	12	11	4	2	1	3.23
Total	743	463	135	64	45	31	100

3.5. Quality Assessment (QA)

QA is an important criterion every systematic review must employ to address any unfairness in the article selection process. Study [22] referred to it as a process that brings about reliability and trustworthiness to the selected articles and the meta-analyses that come thereof using a set of conditions that articles must align with after the inclusion and exclusion criteria. This ensures that primary studies have enough information to answer the research questions. Each criterion is called 'QAC', which stands for Quality Assessment Criteria. In this systematic review, the following quality assessment questions stated in Table 3 were used to check the validity of the selected studies.

Table 3. Quality Assessment Criteria.

Code	Quality Assessment Criteria (QAC)
QAC1	Does the study use ML approaches to develop recommender systems?
QAC2	Are the data sources for training and testing the recommender system clearly described?
QAC3	Does the study have a well-defined methodology?
QAC4	Are the machine learning algorithms and evaluation methods used specified?
QAC5	Are feature engineering or optimization techniques used?

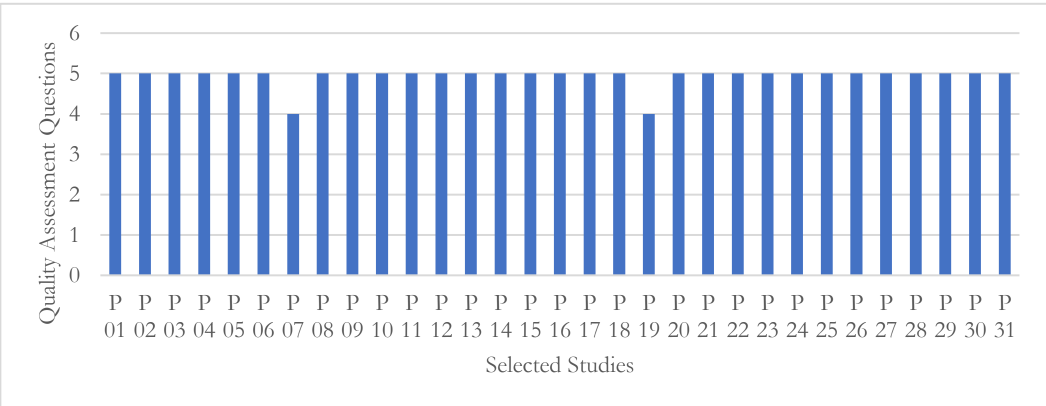

Figure 2. Quality Assessment Visualization

A strict quality assessment scoring procedure was employed to evaluate the relevance and quality of each study based on how well it addresses the research questions. A score of 1 is assigned if a study meets the criterion and 0 if it does not. Overall, a maximum of 5 points would be awarded to studies with detailed and excellent descriptions across all the criteria. In contrast, the lowest score was awarded to studies that didn't meet any of the criteria. To avoid ambiguous situations, the QAC is strict, such that an article either meets a criterion or does not. That is, there is no room for partially satisfied conditions to ensure that only high-quality articles are included in the analysis. Only studies that met a certain average score threshold of 60% were included; studies that did not score greater than the given threshold were not included in the study. After conducting the quality assessment for each primary study, the total score of the selected primary studies was greater than 60% against each QAC, as shown in Figure 2. Notably, using a robust article screening method, all 31 articles were returned validated for onward meta-analysis.

3.6. Data Extraction

Data extraction entails systematically collecting pertinent information from studies to address research questions [23]. This section outlines our approach to extracting data from selected studies using a standardized data extraction form. We employed a predefined template to gather details such as study title, authors, publication year, utilized databases, and study objectives. Also, we gathered key information regarding data sources, feature engineering techniques, machine learning algorithms, and optimization techniques. Additionally, performance metrics and the educational settings in which the recommender systems were deployed were extracted. Each study's strengths, limitations, and key findings were also recorded. This detailed extraction allowed for a comprehensive analysis of trends, challenges, and opportunities in machine-learning approaches to course recommendation systems. For instance, the analytical insights about the article, database distribution, and the year-wise analysis of the articles considered are shown in Figure 3 and Figure 4, respectively. Other analyses concerning the research questions are presented in Section 3.

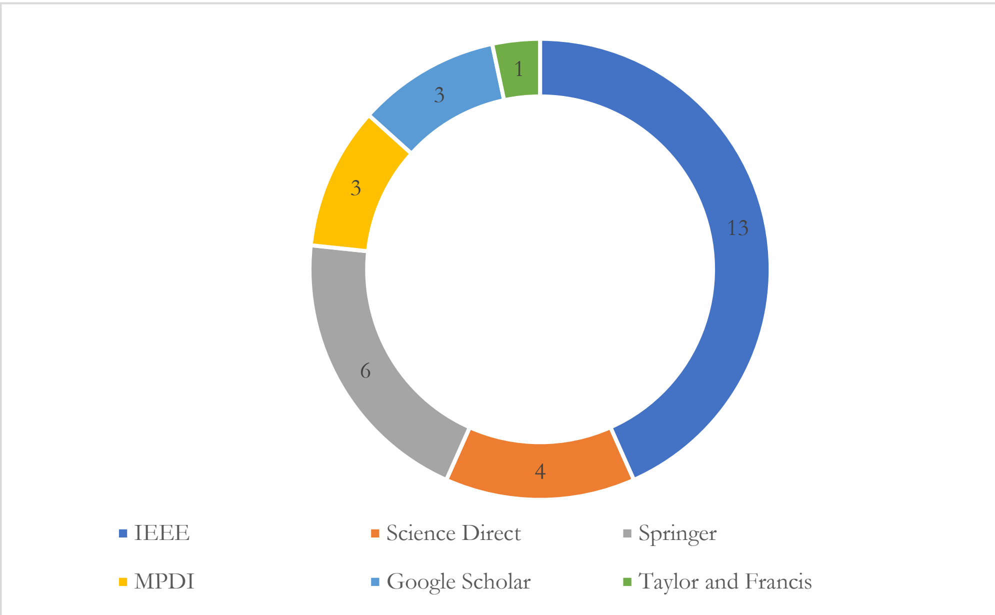

Figure 3. Studies Selected Across Databases

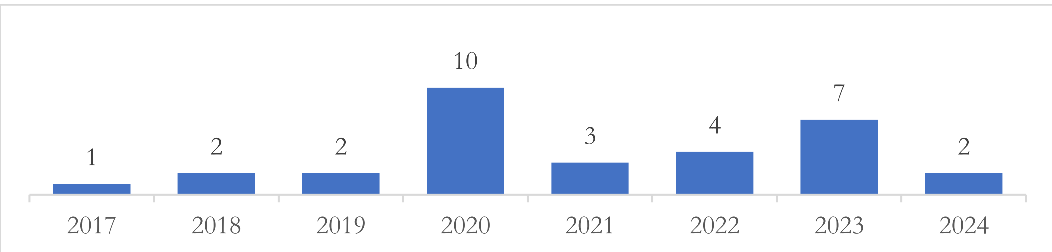

Figure 4. Yearly Distribution of Selected Articles

In Figure 4, it is clear from the selected studies that research on recommender systems continued to gain researchers' attention with a sharp increase in the years 2020 and 2023. The peak in 2020 can be likened to the COVID-19 plague which brought about a compulsory shut-down worldwide. It may not be out of place to assert that the COVID-19 pandemic gave researchers enough time to conduct research due to the compulsory stay-at-home order without the usual work schedules.

4. Results and Discussion

The analysis is based on the screened and finally selected articles for the research questions in section 1 of this systematic review. It is important to note that not all the studies considered for the review reported every critical analytical component evaluated in this review, including feature engineering and optimization techniques or the educational settings where the models were deployed. Consequently, each subsection's analysis relies exclusively on the data available in the respective studies. The variation in reporting implies that not all studies will appear across all results sections.

4.1. What are the primary data sources for course recommendation systems?

Table 4. Data sources for developing course recommender systems

Data Sources	Research(s)	Qty
Open University Learning Analytics Dataset	[24], [25]	2
Real-World Datasets from Universities	[5], [26], [27], [28], [29], [30], [31], [32], [33], [8]	10
MOOC-Specific Datasets and Open Online Courses	[13], [34], [35], [36], [37], [38], [39], [40], [41],	9
University-Specific Datasets	[7], [42], [43], [44], [45], [46]	6
Unspecified Sources	[47], [48], [49], [50]	4

The findings from Table 4 demonstrate that researchers often create and evaluate course recommender models utilizing MOOC-specific datasets and real-world datasets from academic Institutions, each of which has nine appearances across studies. As [34] and [36] noted, the datasets from platforms like Coursera and Udemy were crucial for understanding the behaviors of learners, whereas [26] and [5] presented comprehensive student data such as enrollment, grades, and demographics for developing recommender models. Also, University-Specific Datasets appeared 5 times, capturing specific institutional data as seen in the study [42]. Four studies could not report the data sources used in their research.

4.2. What feature engineering methods have been applied in a course recommender model?

This study assessed all these approaches across the selected literature, as shown in Table 5.

Table 5. Feature engineering techniques for implementing recommender systems

Feature Engineering (s)	Research(s)	Qty
Pearson Correlation Coefficient and Feature Discretization	[42]	1
Course Attribute Extraction, User Behavior Extraction, Preference Information Regression	[32]	1
Feature Binarization	[42], [45]	2
Lemmatization, Tokenization	[48]	1
Label Encoding	[31]	1
Normalization	[13], [30], [31], [33], [34], [40], [43], [44], [46]	9
Class Reduction, Data Resampling, Feature Creation, Feature Deletion	[30]	1
Modified One Source Denoising	[25]	1

Table 5. continue

Feature Engineering (s)	Research(s)	Qty
Attention method	[24], [46]	2
Correlation-based Feature Selection	[47]	1
Clustering and labeling patterns	[41]	1
Negative sequence pattern mining and convolutional sequence embedding	[35]	1
Lowercase conversion, Removing punctuation, Stripping white spaces	[27]	1
One-Hot Encoding	[39]	1
Compression techniques for long-term and short-term interests	[24]	1
Glove embedding technique	[38]	1
Forward selection and backward elimination	[29]	1
Lexical feature extraction, node2vec	[28]	1
Cosine Similarity	[36]	1

As stated in Table 5, numerous feature engineering techniques have been employed in the machine learning course recommender system. Among the techniques used, normalization was the most utilized across nine studies, indicating its widespread application. Out of 31 studies considered for the review, 23 reported using feature engineering techniques.

4.3. What are the machine learning algorithms primarily adopted in course recommender systems?

Table 6. Machine learning algorithms used in the selected studies

S/N	Methods (s)	Research(s)	Qty
1	Sparse Linear Method	[5]	1
2	Neural Collaborative Filtering	[13], [34]	2
3	Improved Neural Matrix Factorization	[34]	1
4	Support Vector Machine	[42], [30], [25]	3
5	Quadratic Discriminant Analysis	[42]	5
6	Random F	[42], [30], [47],[41],[36]	5
7	K-Nearest Neighbor	[36], [26], [13], [45], [47], [30], [42]	7
8	Logistic Regression	[26], [30], [42], [47]	4
9	Deep Neural Network	[7], [49]	2
10	Multi-Layer Perceptron	[24], [46], [49]	3
11	Apriori Frequent Pattern Mining	[27]	1
12	Naïve Bayes	[26]	1
13	Decision Tree	[26], [29], [30], [47]	4
14	Multi-Label K-Nearest Neighbor	[45]	1
15	DeepFM	[50]	1
16	Gradient Boosting Classifier	[30]	1
17	Density-Based Spatial Clustering of Applications	[25]	1
18	Transudative Support Vector Machine	[25]	1
19	Bidirectional Long Short-Term Memory	[24], [25]	2
20	Long Short-Term Memory	[24], [46], [48]	3
21	XGBoost	[47]	1
22	Gradient Boosting	[30], [47]	2
23	Gaussian Naïve Bayes	[47]	1
24	CatBoost	[47]	1
25	LightGBM	[47]	1
26	Neural Network	[33]	1

Table 6. continue

S/N	Methods (s)	Research(s)	Qty
27	Neural Collaborative Filtering	[34]	1
28	Apriori	[27], [41]	2
29	Matrix Factorization	[43]	1
30	Deep Convolutional Neural Network	[35]	1
31	K-means.	[27]	1
32	Deep reinforcement learning	[38], [39]	2
33	Deep Q-learning	[39]	1
34	Deep Reinforcement Recommendation	[38]	1
35	Q-learning	[37], [38], [39]	3
36	Bayesian Probabilistic Tensor Factorization	[28]	1
37	eXtreme Gradient Boosting Regressor	[36]	1
38	Linear Regression	[36]	1

The results from Table 6 show that K-Nearest Neighbors (KNN) appear seven times across studies, such as [13], [26], [42]. The effectiveness of the KNN algorithm in course recommendations stems from its ability to capture user preferences and similarities. Random Forest and Logistic Regression models appear in five studies. According to [30] and [36] Random Forest is well-known for handling complex and high-dimensional data, which makes it useful for making recommendations

4.4. What optimization techniques are commonly used to enhance the performance of machine learning models in course recommender systems?

Table 7. Optimization techniques used in the selected studies

Feature Engineering (s)	Research(s)	Qty
Alternate minimization strategy L0 regularization	[5]	1
Adam Optimizer	[34], [35], [49]	3
Adaptive modeling selection, Grid search	[42]	1
Huber Loss function	[49]	1
GridSearchCV	[31]	1
Modified Anarchic Society Optimization (MASO)	[25]	1
Matrix factorization	[41]	1
Minibatch method, Learning rate adjustment	[25]	1
Stochastic Gradient Descent (SGD)	[28]	1

In Table 7, it is clear that the Adam optimization technique is used more compared to other optimization approaches, as it appears in the studies of [34], [35], [49]. The popularity of this technique could be attributed to its ability to effectively train deep-learning models and handle non-linear relationships in datasets with its adaptive learning rate adjustments, making it highly efficient for complex recommendation tasks [35].

4.5. What evaluation metrics are commonly used to measure the performance of machine learning-based course recommender systems

The evaluation metrics shown in Table 8 are divided into three main categories: classification-based, regression-based, and ranking-based metrics. In classification tasks, precision, recall, and F1 score are among the widely used metrics appearing in 11, 10, and 5 studies, respectively. Precision measures the relevance of recommendations by calculating the percentage of relevant recommended courses. In contrast, recall measures the number of relevant courses that are recommended. F1-score, which balances recall and precision, is helpful, particularly when dealing with imbalanced datasets, which is a common problem in educational data. Also, 8 studies reported the use of accuracy in evaluating recommender models, which could sometimes be deceptive in extremely sparse and unbalanced datasets. Regression metrics like RMSE and MAE were used in 9 and 8 studies, respectively, for continuous predictions like course ratings. While MAE provides a direct average of prediction errors, RMSE penalizes errors. Ranking metrics were also featured prominently in evaluating Top-N recommendation models. Hit rate determines if at least one relevant item is among the Top-N recommendations. Whereas the Normalized Discounted Cumulative Gain (NDCG) takes into cognizance the relevance and position of recommended courses in a ranked list, Average Reciprocal Hit Rank (AVHR), and Mean Average Precision (MAP) further refine it by averaging the ranks of all relevant courses to give a better understanding of the recommender's capacity to rank relevant courses highly. The ranked metrics are very important when recommended courses' position and relevance directly influence the learner's decisions.

Table 8. Evaluation Metrics used in the selected studies

Evaluation Metrics	Research(s)	Qty
Hit Rate	[13], [26], [32], [38], [39], [51]	6
Average Reciprocal Hit-Rank	[13], [51]	2
RMSE	[7], [27], [28], [33], [34], [36], [43], [46], [49]	9
MAE	[7], [13], [27], [28], [34], [36], [43], [49]	8
Accuracy	[7], [24], [26], [29], [30], [44], [46], [48]	8
Precision	[27], [28], [30], [35], [36], [41], [42], [44], [45], [46], [48]	11
F1-Score	[30], [41], [42], [45], [47]	5
Recall	[27], [28], [30], [35], [36], [41], [42], [44], [45], [48]	10
Normalized Discounted Cumulative Gain	[32], [36], [38], [39]	4
Cohen's Kappa	[47]	1
False Discovery Rate	[48]	1
Modified Anarchic Society Optimization	[25]	1
Mean Average Precision	[35]	1
Loss	[24], [46], [47]	3
Mean Reward	[37]	1
Hit Ratio	[34]	1
RME	[26]	1
Click-through rate	[50]	1
Coverage	[40]	1

4.6. In which educational settings are machine learning-based course recommender systems most commonly deployed?

Table 9. Educational settings where course recommender systems are deployed

Education Settings	Research(s)
E-learning environment	[5], [33], [34], [48], [53], [50], [49], [51], [14], [41], [43], [40], [35], [39], [26], [37], [36], [38]
Traditional classroom environment	[27], [8], [45], [32], [31], [52], [46], [44], [30], [29]

From Table 9, it is very important to note that the most commonly used educational setting based on the selected literature is the e-learning environment appearing in 18 studies. This setting, utilized by researchers such as [5], [34], and [48], takes advantage of the vast amounts of data generated through online learning platforms, such as MOOCs, open educational resources, and virtual learning environments. In contrast, traditional classroom environments were employed in 10 studies, including those by [27] and [52] where courses are recommended based on academic performance and structured learning paths within schools and universities.

6. Discussions

One of the 2030 Agenda for Sustainable Development goals of the United Nations is to ensure that all learners acquire the knowledge and skills needed to promote sustainable development. To achieve this, learners must be guided on how to leverage Artificial Intelligence to make academic decisions that will help achieve this objective. This systematic review investigated the machine learning algorithms that are always deployed in developing course recommender systems that will be relevant to students in making academic and career choices. The studies considered for the review were obtained from Seven Databases, as shown in Figure 3, published between 2017 and 2024. The systematic review focused on the Data sources used in developing course recommender systems, feature engineering techniques adopted, and the machine learning models deployed. Other review aspects include the optimization techniques, the evaluation metrics, and the educational environment where such models are deployed. Hence, the discussions concerning each of the research questions are presented below:

Considering Research Question 1, a systematic meta-analysis of different data sources for developing course recommender systems was presented. Institutional-specific datasets are reported as the most frequently used data source, as stated in Table 4. These datasets are often small, imbalanced, or lack social-contextual factors like Students' motivation, aspirations, or socioeconomic background. The lack of standardized, publicly available benchmark datasets hinders model comparison, scalability, cross-institutional evaluation, and generalization. This underscores a significant barrier in the field as the development of scalable course recommender systems is constrained by data quality and availability.

Systematic review question two addresses the feature engineering techniques adopted in making the features of datasets fit for developing a machine learning-based course recommender system. The results from Table 5 show that most studies were largely limited to preprocessing techniques such as normalization and label encoding. Larger numerical range features may significantly affect the model's performance without normalization, leading to biased recommendations [52]. Only a few studies used advanced techniques like unsupervised dimensionality reduction, feature selection, and feature embedding. As a result, many recommender models may be under-optimized and fail to capture more complex and context-aware educational patterns. This implies that model performance is not completely dependent on algorithmic innovation alone, but also on a domain-informed feature construction.

The review Question 3 considered the machine learning models used in all 31 studies for developing course recommender systems. Among the investigated machine learning models, K-Nearest Neighbors (KNN) was the most used algorithm, followed by Random Forest and Logistic Regression. KNN's popularity stems from its simplicity and effectiveness in recommending items based on similarity [57]. Similarly, using an ensemble model like the random forest reflects the preference for robust, interpretable algorithms that can handle diverse and noisy educational datasets. However, the transformer-based and deep learning models are notably underutilized as they appear only in a few studies. This points to a broader methodological trend in studying educational recommender systems. Most implementations favor models with high interpretability and low computational cost, most likely because of dataset limitations, the requirement for explainability in educational settings, and the possibility of deployment in resource-limited institutions. Hence, deep learning models are often optimized for high-dimensional or unstructured data, and their data-hungry architecture may not be well suited for educational datasets, which are often tabular, sparse, and small in scale.

Table 5 answers review question 4, as it is evident that the Adam optimizer was the most used optimization technique considered by some of the selected studies in developing personalized machine learning course recommender systems. Its ability to dynamically adjust learning rates for each parameter helps models converge faster and perform better, even when the data involves high variability, such as user interactions and course preferences [53]. Also, the optimization technique in question typically performs well without requiring extensive manual tuning of hyperparameters, making it easier to implement [54]. Few studies utilized structured optimization techniques like Bayesian optimization, grid search, or the AutoML frameworks. The reproducibility of the reported performance metrics is undermined due to the lack of rigor in hyperparameter tuning. Therefore, models might not be reaching their full potential. Optimization should be considered a foundational step in model development rather than a peripheral task.

Similarly, several performance metrics were used, including classification (Precision, recall, F1-score, and accuracy), regression metrics (RMSE, MAE), and ranking metrics (Hit Rate, NDCG, MAP, ARHR), as precision is reported as the key measuring instrument in evaluating recommender models as shown in Table 6. The findings agree with the research of [45], who used a model-based learning algorithm to develop a recommender system. This study reported precision as the best evaluation metric, producing the most accurate recommendations. While the variety in performance metrics (classification, regression, and ranking) shows the awareness of the multi-dimensional evaluation needs, the diversity indicates a lack of coherence among studies. This underscores the fundamental need for standardized frameworks that evaluate recommender systems based on accuracy and educational relevance and impact on students' academic performance.

Lastly, the findings, as presented in Table 8, show that machine learning-based course recommender systems are most commonly deployed in e-learning environments, unlike traditional classroom settings. The skewness towards a digital learning environment tends to restrict the generalizability of findings to larger educational systems, especially in areas with less developed e-learning infrastructure. From a conceptual standpoint, this implies that such recommendation systems may risk reinforcing inequalities by exclusively serving students with access to digital resources.

6. Challenges and Future Direction

- Limited adoption of machine learning models: Most recommender models use conventional algorithms like KNN, Random Forest, and SVM with little usage of more powerful models like transformer or Deep Learning architectures, which have the potential to provide better personalization. To solve this problem, future studies should focus on developing hybrid models that combine deep learning with domain-specific constraints to accommodate educational data features for real-world deployment across different educational institutions.
- Underutilized feature engineering and optimization techniques: Many models depend on simple data preprocessing and default configurations, which could affect the model's maximum performance. Future research should consider both robust optimization techniques like grid search, AutoML, and Bayesian optimization and automated feature construction strategies like AutoFeat and feature embeddings or collaborate with educators to extract pedagogically meaningful features from raw data.
- Absence of standardization and diversity in datasets: the research findings also show that the datasets mostly used in developing recommender systems are institution-specific, small, with limited access, and lacking contextual features. Future research should focus on creating benchmark and annotated datasets representing diverse learners' demographics.
- Task Mismatch and inconsistent evaluation metric: Numerous studies employ numerous metrics without clear justification or alignment with the recommendation goals. Future research should adopt task-appropriate evaluation frameworks reflecting educational value and technical performance.
- Educational deployment has limited scope: It was also discovered that course recommender models are not widely used outside e-learning platforms, leaving the traditional learning environment underrepresented. Future research should consider expanding recommender system design and validation to various educational contexts, taking cognizance of institutional constraints and existing curricula.

While not explicitly addressed in the review studies, the following are conceptual issues that must guide future development;

- Adaptability and personalization problems: Over-reliance on generic features that do not address individual learning needs is responsible for existing recommender systems failing to provide recommendations peculiar to learners' skills and preferences. As pointed out by [45], the frequent changes in learners' needs and new users tend to struggle with these recommender models; hence, models that incorporate adaptive techniques that continuously refine suggestions based on user behavior can improve the performance of recommender systems.

- Data Privacy and Security: Access to a reasonable and significant amount of learner data is required to develop course recommendation models using machine learning models that need access to significant amounts of user data, which brings about data privacy and security concerns. Protecting personal information is essential in educational settings, particularly when younger learners are involved. Although systems such as [30] recognized the importance of privacy in course recommender model development, they still struggle to secure user data while completely providing personalized recommendations. This gap can be addressed if future studies could focus on implementing privacy-preserving machine learning approaches like differential privacy or federated learning in developing recommender models for course and career choices while guaranteeing accuracy and privacy without exposing learners' sensitive information.
- Dynamic Changes in User Preferences: Static models may struggle to capture user-evolving behavior as learners' preferences can change over time. This challenge is particularly evident in Massive Open Online Courses, where learners might change interests midway through a course. Models such as those proposed by [34] incorporate time information but still face limitations in fully adapting to these changes. Future research should explore reinforcement learning and recurrent neural networks that can capture temporal patterns in user interactions, ensuring that as user preferences evolve, recommendations remain relevant.

7. Conclusions

This systematic review thoroughly synthesizes 31 recent studies spanning from 2017 to 2024 on machine-learning-based courses and career recommender systems, highlighting current trends, methodological flaws, and future opportunities. The review focuses on six key objectives: identifying the sources of datasets, the feature engineering techniques, the machine learning models, the optimization techniques, the evaluation metrics adopted, and the educational settings where these systems were deployed. With the over-dependence on traditional machine learning models like KNN and Random Forest and little experimentation with Deep learning models, the research findings demonstrate that the discipline is still in its developmental stages. Also, the optimization techniques are not thoroughly explored or underreported, while feature engineering techniques are largely basic. The review's findings also show that evaluation metrics are used inconsistently, making it difficult to compare results across studies. While many studies show encouraging results, small and proprietary datasets constrain their practical applicability.

Furthermore, there is little consideration given to traditional or hybrid learning contexts, with the deployment of these systems focusing primarily on e-learning environments. Also, adaptability and personalization problems, data privacy and security, and dynamic changes in user preferences were the identified challenges. The study's results underscore the need for more robust and context-aware methods integrating standardized datasets with adequate learner profiles, adaptive model architectures, and scalable recommendation frameworks supporting institutional adaptability, real-world educational needs, and personalized learning.

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