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RECOMMENDATION ALGORITHMS FOR EDUCATIONAL PREFERENCES: A REVIEW

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Abstract. Educational Recommender Systems (ERS) have become a critical component of modern digital learning environments, offering personalized learning pathways tailored to individual student needs, preferences, and behaviors. These systems utilize a wide range of data sources—including demographic information, academic performance, cognitive characteristics, and behavioral patterns—to recommend relevant courses, learning materials, and strategies that support student engagement and success. This paper presents a comprehensive review of current approaches used in the development of ERS, including collaborative filtering, content-based filtering, hybrid recommendation models, machine learning, deep learning algorithms, knowledge graphs, and explainable artificial intelligence (XAI). Particular attention is given to the advantages and limitations of each approach, as well as key challenges that persist in the implementation of ERS. These include the cold-start problem, data sparsity, scalability issues, lack of transparency in decision-making, and concerns regarding user privacy and algorithmic fairness. The paper also explores practical applications of ERS in higher education and large-scale online platforms such as MOOCs, where such systems have demonstrated positive impacts on learner motivation, retention, and academic performance. Furthermore, the ethical dimensions of educational recommendations—such as inclusivity, bias mitigation, and transparent design—are discussed as essential components of trustworthy and student-centered systems. The review emphasizes the growing importance of adaptable, interpretable, and ethically aligned recommendation models that can evolve with the dynamic nature of modern education. Finally, the study identifies key directions for future research, including the development of reinforcement learning-based systems, improved handling of large and heterogeneous data sets, and the integration of personalized recommendation mechanisms that enhance the overall quality, transparency, and fairness of digital education worldwide.

Key words: Personalized learning, Educational Recommendation Systems (ERS), Collaborative Filtering, Hybrid Models, Large-Scale Datasets, Explainable Artificial Intelligence

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БІЛІМ АЛУДЫ ЖАҚСАРТУ ҮШІН ҰСЫНЫС БЕРЕТІН АЛГОРИТМДЕРГЕ ШОЛУ

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Аннотация: Білім беру бойынша ұсыныс жүйелері (Educational Recommender Systems, ERS) соңғы жылдары цифрлық оқытудың ажырамас құрамдас бөлігіне айналып, жекелендірілген оқыту әдістерін іске асыруға және білім беру сапасын арттыруға айтарлықтай үлес қосып келеді. Мұндай жүйелер студенттердің академиялық үлгерімі, оқу барысындағы мінез-құлық ерекшеліктері, жеке қалаулары, когнитивтік стильдері мен демографиялық мәліметтері сияқты әртүрлі деректерді сараптай отырып, оқыту траекториясын жеке бейімдеуге мүмкіндік береді. Бұл мақалада ERS құруда қолданылатын заманауи әдістерге жан-жақты шолу жасалады. Атап айтқанда, коллаборативті сұрыптау, мазмұнға негізделген сүзгілеу, гибридті модельдер, машиналық және терең оқыту алгоритмдері, білім графтары мен түсіндірмелі жасанды интеллект (XAI) технологиялары қарастырылады. Сонымен қатар, деректердің сиректігі, суық бастау мәселесі, жүйені кеңейту кезіндегі қиындықтар, алгоритмдердің ашықтығы мен пайдаланушылардың дербес деректерін қорғау қажеттілігі сияқты өзекті мәселелер талданады. ERS-тің ашық онлайн-оқыту платформаларында (MOOC) және жоғары оқу орындарында қолданылу мысалдары келтіріліп, олардың студенттердің мотивациясын арттыруға, оқу процесіне тартылуын күшейтуге және оқудан шығу деңгейін төмендетуге ықпал ететіні көрсетіледі. Сонымен қатар, ұсыныстар әділдігі, инклюзивтілік және этикалық тұрақтылық мәселелері де қарастырылады. Авторлар білім беру саласындағы өзгермелі талаптарға бейімделе алатын, икемді, түсінікті және әділ ұсыныс жүйелерін әзірлеудің маңыздылығын атап өтеді. Бұл шолу зерттеу білім беру жүйелерін одан әрі дамытуға негіз бола отырып, ұсыныс жүйелерінің тиімділігін, этикалық жауапкершілігін және жекелендіру деңгейін арттыру жолдарын ұсынады.

Түйін сөздер: Білім беру бойынша ұсыныс жүйелері (БҰЖ), жеке оқыту, коллаборативті сұрыптау, гибридті модельдер, түсіндірмелі жасанды интеллект (XAI), кең көлемді деректер жиынтығы, ұсыныс дәлдігі

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ОБЗОР РЕКОМЕНДАТЕЛЬНЫХ АЛГОРИТМОВ ДЛЯ ОБРАЗОВАТЕЛЬНЫХ ПРЕДПОЧТЕНИЙ

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Аннотация: Образовательные рекомендательные системы (Educational Recommender Systems, ERS) в последние годы становятся неотъемлемой частью цифровых образовательных платформ, так как позволяют реализовать персонализированный подход к обучению и повысить его эффективность. Эти системы используют современные алгоритмы анализа данных и искусственного интеллекта для подбора учебных материалов, курсов и индивидуальных траекторий обучения, опираясь на широкий спектр информации: академическую успеваемость, поведенческие особенности, предпочтения, когнитивные стили, а также демографические данные обучающихся. Настоящая статья представляет собой всесторонний обзор современных подходов к построению ERS, включая коллаборативную и контентную фильтрацию, гибридные модели, алгоритмы машинного и глубокого обучения, применение графов знаний и объяснимого искусственного интеллекта (XAI). Рассматриваются ключевые проблемы, с которыми сталкиваются такие системы: эффект «холодного старта», разреженность данных, сложности масштабирования, необходимость обеспечения прозрачности алгоритмов и защиты персональных данных. Также анализируются практические примеры применения ERS в контексте онлайн-обучения и высшего образования (в том числе на платформах MOOCs), где системы рекомендаций демонстрируют высокую результативность, способствуя снижению отсева студентов, повышению их мотивации и вовлечённости в учебный процесс. Отдельное внимание уделено вопросам этики, инклюзии, а также справедливости в рекомендациях. В статье подчёркивается необходимость развития устойчивых, адаптивных и интерпретируемых моделей, способных учитывать изменения в образовательных потребностях и контексте. Представленное исследование не только систематизирует существующие подходы, но и обозначает направления дальнейших разработок, направленных на повышение качества, прозрачности и персонализации цифрового образования на глобальном уровне.

Ключевые слова: образовательные рекомендательные системы (ERS), персонализированные обучение, коллаборативная фильтрация, гибридные модели, объяснимый ИИ, крупномасштабные наборы данных, точность рекомендации

Introduction. Educational systems with recommending functionalities are very popular and their application and usage are getting wider according to their capability to proffer materials, which meets individual preferences of learners. By performing analyze on data like materials of past courses, contents of searches by learners ERS generate suggestions using filtering types, like collaborative, content-based and hybrid. However, challenges such as the cold-start problem and data sparsity persist, particularly for new users or courses (Masthoff, 2023; Thammarak, Kesornsit, & Sirisathitkul, 2024; Zhou & Zhang, 2024).

Hybrid systems that combine CF and CBF have demonstrated improvements in addressing these limitations, offering more accurate and robust recommendations (Shuang & Hang, 2024; Alahmadi & Alruwaili, 2021). In addition, deep learning and matrix factorization methods like Singular Value Decomposition (SVD) have significantly enhanced the performance of ERS, especially in large-scale environments like MOOCs (Wu, 2023; Alfaifi, 2024).

The inclusion of knowledge graphs and explainable AI (XAI) offers further advancements by providing more personalized, context-aware recommendations and ensuring transparency in the recommendation process (Shuang et al., 2024; Zheng, 2022; Yazdi et al., 2024). While progress has been made, challenges related to privacy, data management, and recommendation quality remain, requiring ongoing research to further enhance the effectiveness of ERS (Dhananjaya, Goudar, Kulkarni, & Rathod, 2024; Xiong, Li, Liu, Chen, Zhou, Rong, & Ouyang, 2024).

Materials and Methods. Implication of recommender systems to educational process requires significant efforts due to the fact that it has enormous aspects. The next research questions were studied in the current paper in order to obtain majority of these aspects (Table 1):

Table 1. Research questions

Research questions
Background and Key Concepts
Main Approaches to Educational Recommendations
Challenges in Educational Recommender Systems
Case Studies and Applications
Evaluation of Educational Recommender Systems
Future Directions and Research Gaps

Approaches to Material Search. Relevant material was sourced using a methodical strategy to guarantee a thorough review. The following techniques were applied:

1. Database Selection: Google Scholar, Elsevier's ScienceDirect, IEEE Xplore, ACM Digital Library, and Springer were used as major academic databases. For the most recent scientific findings, preprint sources such as arXiv were also investigated.

2. Method of Search: To find pertinent material, a mix of Boolean operators and keywords was employed. Among the sample search terms were: "Educational recommender systems" AND "personalized learning"

- "Collaborative filtering in education" OR "content-based recommendation for students"
- "Challenges in adaptive learning platforms"
- "Hybrid recommendation models in MOOCs"

Inclusion and Exclusion Criteria:

- **Inclusion Criteria:** Peer-reviewed journal articles, conference papers, and authoritative surveys published in the last decade (2020-2025) focusing on recommender systems for educational settings.
- **Exclusion Criteria:** Papers that do not explicitly discuss recommendation algorithms in education, duplicate studies, and works that lack empirical validation.

Selection Process: Titles and abstracts were screened to determine relevance. Full-text articles were reviewed if they contained significant discussions on educational recommender systems.

Classification of Sources: The collected materials were categorized into different themes aligned with the research questions in Table 1. This ensured structured analysis and synthesis of information.

Methodology. To answer the research questions, an integrative literature review methodology was employed. The process involved:

- **Thematic Analysis**: Identifying and grouping themes such as user modeling, algorithmic approaches, and evaluation techniques.
- **Analyzing by comparing**: compare different techniques of recommendations in order to detect their strength, weakness and possible contexts of application.
- **Case Study Review**: Examining real-world implementations of educational recommender systems to assess their impact.

By employing these methodologies, this study provides a structured and comprehensive analysis of recommendation algorithms in educational settings, ensuring coverage of both theoretical and applied aspects of the field.

2.1 Background and Key Concepts

2.1.1 Overview of Recommender Systems. Recommender systems (RS) are software tools and techniques designed to assist users in making decisions by providing personalized suggestions. The types of systems analyze behaviors of users according to their previous activities in a system in order to give suggestions and recommendations about products, services, information resources and courses. Typically, RS employ methods like collaborative filtering, content-based filtering, and hybrid approaches, each with its own strengths and limitations (Aucancela, 2023; Li, Zhang, & Zhang, 2021; Kamal et al., 2024; Urdaneta-Ponte et al., 2021).

The focus Collaborative Filtering (CF) is directed to the interaction of users with items. This approach generalized the preferences of users with similar behaviors for proposing recommendations. The main problem in the usage of this method can the sparsity of data and cold-start issue. On the other hand, Contend-Based Filtering (CBF) pays attention to the attributes of items and makes suggestions on the basis of user's interaction with cognate items in the past. While CBF can handle new items effectively, it may struggle with offering diverse suggestions (Zhou et al., 2024; Alahmadi et al., 2021; Xiong et.al., 2024). Hybrid systems combine CF and CBF techniques to address their respective shortcomings, offering improved accuracy and robustness (Thammarak et al., 2024; Alahmadi et al., 2021; Yazdi et al., 2024).

The wide use of recommendation systems can be found in domains like tourism, healthcare, e-commerce and education. Their ability to enhance user experience, decision-making, and engagement has positioned them as crucial tools across industries (Urdaneta-Ponte et al., 2021; Xiong et al., 2024).

2.1.2 Distinction Between General Recommender Systems and Educational Recommender Systems. Educational recommender systems (ERS) are a specialized subset of RS designed to support educational decision-making by providing personalized recommendations for courses, learning materials, career paths, and other academic resources. Unlike general RS, which often prioritize maximizing user satisfaction or sales, ERS focus on improving educational outcomes, engagement, and retention rates (Aucancela, 2023; Butmeh & Abu-Issa, 2024; Dhananjaya et al., 2024).

In order to create suitable recommendations to learners, ERS usually consume unique types of data like demographic information, learning behaviors and academic rates. These systems pursue the aim to solve specific issues in education like helping students guiding suitable course, improve the development of their various skills and the rates of possible dropouts. Techniques such as collaborative filtering, content-based filtering, and hybrid models are commonly employed in ERS, with an emphasis on integrating domain-specific knowledge and learner preferences (Butmeh et al., 2024; Shuang et al., 2024).

One key distinction is the importance of pedagogical considerations in ERS. These types of systems basically use educational theories in their core logic to meet learners expectations and enhance their capabilities, the examples example these theories can be cognitive diagnosis and knowledge mapping (Shuang et al., 2024; Butmeh et al., 2024; Silva et al., 2022). Furthermore, Educational Recommender Systems (ERS) are progressively incorporating sophisticated methodologies, such as deep learning and knowledge graphs, to improve recommendation precision and better accommodate the dynamic needs of learners (Wu, 2023; Zheng, 2022; Guo et al., 2024).

2.1.3 Common Data Types Used in Educational Recommender Systems. ERS rely on diverse data types to deliver personalized and effective recommendations. Commonly used data types include:

1. Demographic Data: Information such as age, gender, and location helps contextualize recommendations, ensuring relevance to the learner's background and circumstances (Butmeh, et al., 2024; Dhananjaya, et al., 2024; Yazdi, et al., 2024).
2. Academic Data: This includes grades, test scores, and course enrollments, providing insights into the learner's academic performance and progress (Phalle & Bhushan, 2024; Dhananjaya, et al., 2024; Xiong, et al., 2024).
3. Behavioral Data: Data on learners' interactions with educational platforms, such as time spent on tasks, resource usage patterns, and engagement levels, helps model preferences and predict future needs (Ma et al., 2023; Phalle, et al., 2024; Xiong, et al., 2024).
4. Cognitive and Learning Preferences insights into learners' knowledge levels, cognitive styles, and favored instructional strategies facilitate the generation of personalized recommendations tailored to their unique abilities and learning objectives (Thammarak, et al., 2024; Rahman et al., 2022; Guo, et al., 2024).

By synthesizing these data dimensions, Educational Recommender Systems (ERS) can construct detailed learner profiles, thereby supporting the creation of recommendations that not only improve learning outcomes but also effectively mitigate issues like the cold-start problem and information overload (Thammarak, et al., 2024; Alahmadi et al., 2021; Raza et al., 2024).

2.2 Main Approaches to Educational Recommendations

2.2.1 Collaborative Filtering (CF). Collaborative Filtering (CF) is a prominent methodology in recommendation systems, particularly in educational recommender systems (ERS). It leverages the preferences and behaviors of users to predict items or services that may interest others with similar patterns. CF operates primarily through two approaches: **user-based filtering** and **item-based filtering**.

- **User-based filtering** identifies users with similar preferences or behaviors. Recommendations are made based on what similar users have liked or interacted with.
- **Item-based filtering** analyzes relationships between items, recommending items that are closely related to those a user has previously interacted with.

CF can effectively propose personalized recommendations especially if there is available a big amount of user-interaction data. For instance, it is frequently employed in course recommendation systems, where courses preferred by users with similar profiles are highlighted as beneficial options (Aucancela, 2023; Butmeh et al., 2024; Zhou & Zhang, 2024; Dhananjaya, et al., 2024) However, CF faces significant challenges:

- **Data sparsity**: When user interaction data is limited, the system struggles to make accurate predictions.
- **Cold-start problem**: The absence of sufficient data for new users or items hinders recommendation accuracy.
- **Scalability**: As datasets grow, the computational cost increases, requiring optimization to maintain efficiency.

To overcome these challenges, researchers propose hybrid approaches that combine CF with other methods, such as content-based filtering, and the integration of trust metrics to enhance accuracy and adaptability (Alahmadi & Alruwaili, 2021; Dhananjaya, et al., 2024; Xiong, et al., 2024). To tackle these issues, some research recommends using hybrid approaches and integrating trust metrics to improve the accuracy and adaptability of recommendations (Raza et al., 2024).

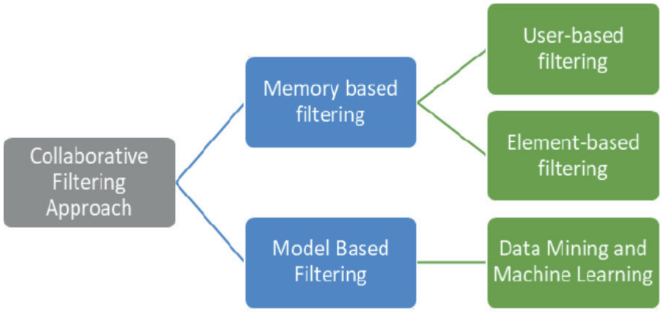

Figure 1 – Categorization of the collaborative filtering approach (Aucancela, 2023)

2.2.2 Content-Based Filtering (CBF). Content-Based Filtering (CBF) relies on analyzing item attributes to recommend items similar to those a user has interacted with in the past. It utilizes algorithms such as decision trees and Bayesian classifiers to match user preferences(Figure 2) with item features, including course topics, difficulty levels, or skill requirements (Zhou & Zhang, 2024; Alahmadi & Alruwaili, 2021). CBF's strengths lie in its ability to handle new users by leveraging their explicitly provided preferences and its independence from other users' data.

However, CBF is prone to overspecialization, where the system repeatedly recommends items similar to those already consumed, leading to a lack of diversity (Zhou & Zhang, 2024; Xiong, et al., 2024). For example, in educational settings, CBF might recommend courses closely aligned with a user's past selections without introducing diverse learning opportunities. Additionally, CBF struggles with new item recommendations since it relies on pre-existing item descriptions. Addressing these challenges often involves hybrid methods that combine the strengths of multiple approaches (Zhou & Zhang, 2024; Dhananjaya, et al., 2024).

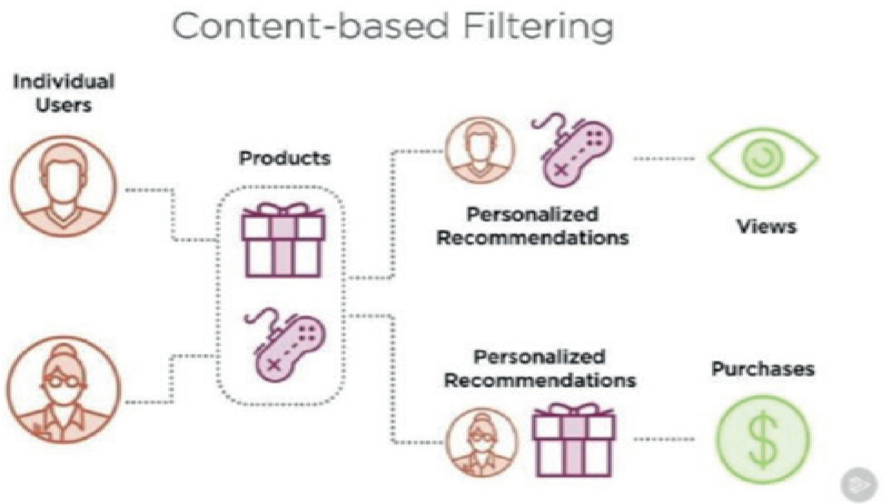

Figure 2 – Content-based Filtering (Zhou & Zhang, 2024)

2.2.3 Hybrid Methods

Hybrid recommendation systems integrate multiple approaches, such as CF and CBF, to overcome their individual limitations and enhance recommendation quality. For instance, hybrid systems can mitigate CF's cold-start problem by incorporating content-based techniques to generate recommendations for new users or items. They can also reduce CBF's (Figure 3) overspecialization by introducing diversity through collaborative methods (Thammarak, et al., 2024; Zhou & Zhang, 2024; Alahmadi & Alruwaili, 2021; Yazdi, et al., 2024).

Several hybridization techniques are employed in ERS, including weighted, switching, mixed, and feature augmentation methods. These approaches combine

CF and CBF dynamically, optimizing performance based on user data and context (Alahmadi & Alruwaili, 2021; Yazdi, et al., 2024). For example, a hybrid attribute-based system tested in an e-learning environment successfully integrated user preferences, learning styles, and knowledge levels to recommend personalized courses while addressing data sparsity and cold-start challenges (Thammarak, et al., 2024). Such systems have demonstrated superior accuracy and adaptability, particularly in addressing diverse learner needs and preferences (Butmeh, et al., 2024; Thammarak, et al., 2024).

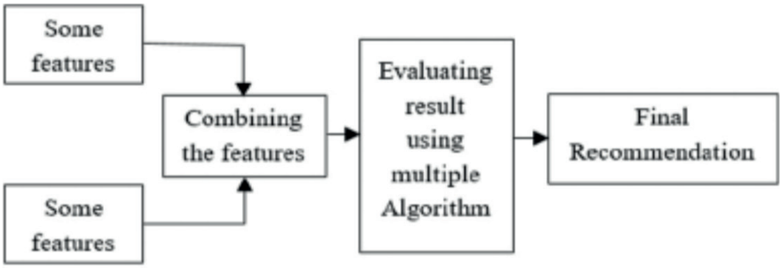

Figure 3 – Hybrid Recommendation System (Alahmadi & Alruwaili, 2021)

2.2.4 AI-Based Techniques

AI-based techniques have transformed educational recommendations by introducing advanced methods like machine learning (ML), deep learning (DL), and knowledge graphs. ML algorithms, including decision trees, random forests, and gradient boosting, have been effectively applied to match students with suitable courses based on their skills and preferences. These methods enhance recommendation accuracy by addressing imbalanced data and incorporating dynamic user behavior (Phalle & Bhushan, 2024).

Deep learning techniques, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, have further advanced ERS by capturing complex patterns in user interactions and preferences. For instance, deep learning models like DeepFM and Bidirectional LSTM have demonstrated high performance in personalized course recommendations, addressing cold-start issues and improving temporal dynamics (Masthoff, 2023; et al., 2024).

Knowledge graphs (KGs) offer another innovative approach by structuring data into semantic networks, enabling more precise and context-aware recommendations. In educational contexts, KGs have been used to address data sparsity and enhance adaptability by combining semantic similarity with item features. For example, the TransAR-CF model improved recommendation accuracy and user satisfaction by leveraging KGs for course recommendations in higher education (Shuang et al., 2024; Rahman et al., 2022).

The integration of these AI-based techniques has significantly enhanced the scalability, accuracy, and personalization of ERS, addressing challenges like the cold-start problem, data sparsity, and scalability while ensuring a more effective and engaging learning experience (Shuang, et al., 2024; Rahman, et al., 2022; Guo, et al., 2024; Raza et al., 2024).

2.3 Challenges in Educational Recommender Systems

Educational Recommender Systems (ERS) face several challenges that limit their efficiency, scalability, and user satisfaction. Below, we discuss the most pressing issues and explore proposed solutions based on the latest research.

2.3.1 Cold-Start Problem

The cold-start problem arises when ERS encounter new users or items with insufficient data for accurate recommendations (Thammarak, et al., 2024; Yazdi, et al., 2024). Traditional collaborative filtering (CF) methods rely heavily on user interactions, making it difficult to generate recommendations for new learners or courses. Hybrid models, which combine CF with content-based filtering (CBF), have been widely adopted to address this challenge (Alahmadi & Alruwaili, 2021). For example, the hybrid attribute-based system proposed integrates user preferences, learning styles, and knowledge levels to create more accurate recommendations for new users (Thammarak, et al., 2024). Knowledge graphs, as highlighted, also help mitigate this issue by providing a semantic understanding of relationships between users and items, enriching the recommendation process (Shuang & Hang, 2024).

2.3.2 Data Sparsity and Scalability

Data sparsity refers to the lack of sufficient user-item interactions, which hinders the performance of CF algorithms (Butmeh, et al., 2024; Xiong, et.al. 2024). Matrix factorization techniques, such as singular value decomposition (SVD) and BiVAE, have been effective in addressing sparsity by capturing latent user and item features (Aldayel et al., 2023; Kamal, et al., 2024). Scalability is another critical challenge, particularly in large-scale educational systems. Distributed computing approaches, including the use of parallel processing and cloud-based infrastructures, have been proposed to improve scalability (Phalle & Bhushan, 2024). These methods enable ERS to process vast datasets efficiently, ensuring timely and relevant recommendations for a growing user base.

2.3.3 Personalization

Personalization is central to ERS, aiming to tailor recommendations to individual learning needs and preferences. However, achieving true personalization is challenging due to the dynamic nature of learners' goals and behaviors (Alfaifi, 2024; Guo et al., 2024). Advances in machine learning (ML) and deep learning (DL) have significantly enhanced the ability of ERS to adapt to individual learning paths.

This study proposes a dynamic recommendation system that leverages bidirectional LSTM networks in combination with mindfulness mechanisms to effectively model and adapt to both the short-term behaviors and long-term preferences of users (Guo et al., 2024). Another approach introduces a hybrid method that clusters students based on their multidimensional skill profiles, aiming to generate more personalized and precise recommendations tailored to each learner (Alfaifi, 2024).

2.3.4 Privacy and Ethical Issues

Privacy and ethical considerations play a crucial role in educational recommendation systems (ERS), particularly when dealing with sensitive student data. Ensuring transparency, fairness, and robust data protection is essential for maintaining user trust and adhering to ethical standards. Research indicates that privacy-preserving technologies, such as differential privacy and encryption techniques, can effectively safeguard user information. At the same time, ongoing monitoring is required to address ethical concerns like algorithmic bias and disparities in access to personalized learning opportunities. User-centered design methodologies are seen as a promising direction for developing fair, trustworthy algorithms and promoting equity in educational settings (Xiong, et.al., 2024).

2.4 Case Studies and Applications

2.4.1 Case Study 1: Course Recommendation Systems in Higher Education

In recent years, course recommendation systems in universities have become a subject of considerable interest among researchers. A systematic review of publications over the past decade identified collaborative filtering as the predominant approach in the development of such systems, with hybrid methods and content-based filtering also being widely applied. These systems make recommendations based on student demographics, academic performance, and personal learning preferences. They have proven to be highly effective in improving retention rates, increasing student engagement, and supporting the creation of personalized learning pathways. For example, several systems use demographic data to tailor course recommendations, fostering better learning experiences for students. Future research directions include exploring multi-view data approaches and incorporating fairness in recommendation processes (Butmeh et al., 2024; Dhananjaya et al., 2024; Thammarak et al., 2024).

2.4.2 Case Study 2: MOOC Recommendation Systems

Massive Open Online Course (MOOC) recommendation systems have gained considerable attention due to their potential to personalize learning at scale. DeepFM and DORIS are two prominent deep learning-based systems used to recommend courses in MOOCs. These systems are designed to overcome common challenges such as cold-start issues, scalability, and data sparsity. DORIS, in particular, leverages deep learning techniques, including DeepFM and TextRank, to enhance recommendation accuracy by processing textual data. The system has shown significant improvements in recommending courses that match learners' preferences and needs. These systems utilize personalized algorithms to suggest courses, taking into account dynamic user preferences and interactions with educational content. Further improvements could focus on integrating advanced deep learning techniques and addressing real-time user feedback to refine recommendations (Zheng, 2022; Yazdi, et al., 2024;Wu, 2023).

2.4.3 Case Study 3: Personalized Learning in E-Learning Platforms

Personalized learning systems in e-learning platforms aim to optimize the educational experience by tailoring content and resources to individual learners. An attribute-based hybrid recommendation system, which combines collaborative filtering and content-based approaches, has been proposed to address the commonly encountered cold start problem in e-learning environments. This approach builds models of both users and courses by taking into account learners' preferences, cognitive styles, and prior knowledge. Empirical studies have demonstrated that when integrated with machine learning techniques—particularly decision trees and random forests—this method proves effective in delivering targeted course recommendations. The use of machine learning algorithms enhances the accuracy of predicting students' course preferences, which in turn contributes to improving the quality of the learning process. Personalized recommendations support students by suggesting courses aligned with their current needs and academic goals (Butmeh et al., 2024; Thammarak, et al., 2024; Phalle & Bhushan, 2024).

2.5 Evaluation of Educational Recommender Systems

2.5.1 Metrics for Evaluation

The evaluation of educational delivery systems (ERS) requires the use of various performance indicators to determine their accuracy and effectiveness. The most commonly used indicators include precision, recall, accuracy, novelty, and diversity. Accuracy and recall — are important for assessing the compliance of the courses offered with user demand, and accuracy — indicates how correctly the system can predict user preferences. Innovation and Variety also play an important role, as they characterize the ability of the system to provide different recommendations, and not monotonous ones, which, in turn, will improve the overall user experience. These metrics help deliver content that is relevant, diverse, and meaningful, thereby improving user satisfaction and engagement (Li et al., 2024; Butmeh et al., 2024; Shuang et al., 2024).

2.5.2 Evaluation Approaches

Various assessment methods are used to evaluate the performance of educational offering systems (ERS). Prediction accuracy is usually determined by metrics such as mean absolute error (MAE) and mean square root error (RMSE), which measure the difference between predicted ratings and actual user feedback. In addition, user-oriented assessment approaches based on surveys and user opinions play an important role in assessing the subjective quality of recommendations. These methods allow you to assess how well the recommendations meet the needs and expectations of users.

In addition, modern assessment methods based on the theoretical foundations of decision-making are being studied, which make it possible to comprehensively assess the performance of the system, taking into account factors such as user satisfaction, adaptive capabilities of the system and long-term efficiency (Li et al., 2024; Butmeh et al., 2024; Urdaneta-Ponte et al., 2021).

2.5.3 Challenges in Evaluation

Assessment of the effectiveness of educational systems (ERS) presents a number of difficulties, primarily due to the complex and multidimensional nature of educational data. Furthermore, the diversity of students' needs and preferences necessitates the creation of a comprehensive evaluation system that can capture the varying impacts of recommendations in different educational contexts. Additionally, ethical considerations and ensuring fairness remain crucial issues, particularly when processing students' confidential data. Researchers are exploring multidimensional evaluation systems that better capture the nuances of educational recommendations, including factors such as diversity, fairness, and privacy (Butmeh et al., 2024; Dhananjaya et al., 2024; Xiong et.al., 2024).

Results and discussion. One of the most promising areas of future research in educational recommender systems (ERS) is the integration of advanced artificial intelligence (AI) models such as learning reinforcement, deep learning and neural networks. According to recent research, MOOC and e-learning environments are deep learning approaches such as convolutional neural networks (CNN), repetitive neural networks (RNNs), and long-term short-term memory (LSTM) architectures that demonstrate important potential in improving the accuracy of representations in contexts such as (Wu, 2023; Alfaifi, 2024). It still requires the study of dynamic and adaptive recommendation processes that can continuously learn from the models of users of artificial intelligence systems and provide personalized course recommendations in real time. In addition, the ability to optimize recommendation systems by creating a responsive educational environment has an impact on changes in the preferences and learning behavior of users of reinforcement learning (Wu, 2023; Guo et al., 2024). Future research aims to provide personalized learning pathways, improving long-term learning outcomes, while developing the use of reinforcement learning based on the student's progress.

One of the main problems in environments where new users or elements (e.g. courses) are often introduced remains the problem of cold start education recommendation systems (ERS). To solve this problem, hybrid models and approaches are offered on the following eLearning and MOOC platforms. In solving cold startup problems, attribute-based hybrid recommendation systems that combine collaborative filtering into content with methods using user data and element attributes to create recommendations for new users or courses have shown promising results (Thammarak, et al., 2024; Phalle et al., 2021). In addition, machine learning techniques such as decision trees and random forests that group elements based on common features are used to improve scalability and offer quality by working with large data sets (Phalle & Bhushan, 2024). Continued development in this area should focus on integrating new data sources and improving the adaptability of these models to handle cold-start problems across diverse educational contexts.

As ERS become more prevalent in personalized education, addressing ethical concerns and ensuring data privacy are crucial. This is due to the large accumulation of personal and academic data needed to personalize learning, especially confidential data of minors and students, which raises serious concerns about confidentiality. The researchers noted the importance of designing recommendation systems that provide clear and meaningful recommendations while ensuring the protection of users' privacy. At the same time, in the development of artificial intelligence models, special attention should be paid to ensuring that the recommendations offered by educational systems (ERS) are fair and impartial and that they are transparent and interpretable in order to build user trust. From the point of view of ethical issues, the risk of increasing bias or limiting educational opportunities should also be taken into account (Xiong et.al., 2024). Future research should focus on developing the foundations of ethical artificial intelligence in education, considering recommender systems (ERS) as a tool that contributes to the formation of an inclusive and fair learning environment.

Conclusion. The survey performed on recommendation algorithms used to detect the preferences in education has exposed the immense capacity of recommender systems in empowering the process of personalized learning. The most used approaches like filtering types: collaborative and content-based, and their hybrid types have been used in studies which pursued to offer students accurate recommendations and concurrently address issues and challenges related with development which include the problems of data sparsity, scalability, and cold-start issue. The application of artificial intelligence approaches in the implementation of educational recommender systems have increased accuracy of recommendations and have shown promising results in the improvement of adaptability of ERS. As modern conditions of learning require from students to evolve in their knowledge as fast as possible, the recommendations of e-learning systems are becoming more and more dynamic and this requires sophisticated algorithms, which can easily adapt to behaviors, preferences and growing learning contexts of students.

Future research should focus on the improvement of hybrid approaches, knowledge graphs and building new model architectures of deep learning, because they have shown the possibility of overcoming actual limitations in ERS. Moreover, widening the usage of ERS to various contexts of education can lead to the further improvement of this field. The future pathway of ERS evolution will focus not only on the personalization of recommendations, but it can also play significant role in detecting the gaps and involvement of learners in the diversity of learning environments.

References

Bing Wu, (2023) “Personalized Hybrid Recommendation Algorithm for MOOCs Based on Learners’ Dynamic Preferences and Multidimensional Capabilities”. https://doi.org/10.3390/app13095548 (In English)

Dimah Alahmadi and Fatimah Alruwaili (2021) “Deep Learning for MOOCs Course Recommendation Systems: State of the Art Survey”, vol. 12, issue 11. (In English)

Dhananjaya Gm, R.H. Goudar, Anjanabhargavi A. Kulkarni and Vijayalaxmi Rathod (2024) “A Digital Recommendation System for Personalized Learning to Enhance Online Education: A Review”. https://doi.org/10.1109/access.2024.3369901 (In English)

Felipe Leite da Silva, Bruna Kin Slodkowski, Ketia Kellen Araújo da Silva and Sílvio César Cazella (2022) "A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities". https://doi.org/10.1007/s10639-022-11341-9 (In English)

Fangxia Zheng, (2022) "Personalized Education Based on Hybrid Intelligent Recommendation System". https://doi.org/10.1155/2022/1313711 (In English)

Hala Butmeh and Abdallatif Abu-Issa (2024) "Hybrid attribute-based recommender system for personalized e-learning with emphasis on cold start problem". https://doi.org/10.3389/fcomp.2024.1404391 (In English)

Hadis Ahmadian Yazdi, Seyyed Javad Seyyed Mahdavi and Hooman Ahmadian Yazdi (2024) "Dynamic educational recommender system based on Improved LSTM neural network". https://doi.org/10.1038/s41598-024-54729-y (In English)

Judith Masthoff, (2023) "Hybrid session-aware recommendation with feature-based models", vol. 34. — P. 691–728 (In English)

Madhusree Kuanr and Puspanjali Mohapatra (2021) "Assessment Methods for Evaluation of Recommender Systems: A Survey", vol. 46. (In English)

Karanrat Thammarak, Witwisit Kesornsit and Yaowarat Sirisathitkul (2024) "Predictive Model for Academic Training Course Recommendations Based on Machine Learning Algorithm". https://doi.org/10.5815/ijmecs.2024.03.02 (In English)

Lianhuan Li, Zheng Zhang and Shaoda Zhang (2021) "Hybrid Algorithm Based on Content and Collaborative Filtering in Recommendation System Optimization and Simulation". https://doi.org/10.1155/2021/7427409 (In English)

Luoshuang Shuang and Chu Hang (2024) "A Study on the Role of Knowledge Mapping Technology in Constructing a Knowledge System for Student Management and Promoting Innovation in and Political Education". https://doi.org/10.2478/amns-2024-2364 (In English)

Nabila Kamal, Farhana Sarkar, Arifur Rahman and Sazzad Hossain (2024) "Recommender System in Academic Choices of Higher Education: A Systematic Review". https://doi.org/10.1109/access.2024.3368058 (In English)

Margarita Alejandra Aucancela, (2023) "Educational Recommender Systems: A Systematic Literature Review". https://doi.org/10.22492/issn.2435-9467.2023.74 (In English)

Mashael Aldayel, Abeer Al-Nafjan, Waleed M. Al-Nuwaiser, Ghadeer Alrehaili and Ghadi Alyahya (2023) "Collaborative Filtering-Based Recommendation Systems for Touristic Businesses, Attractions, and Destinations". https://doi.org/10.3390/electronics12194047 (In English)

Ms. Tejashri Sharad Phalle and Prof. Shivendu Bhushan (2024) "Content Based Filtering and Collaborative Filtering: A Comparative Study". https://doi.org/10.53555/jaz.v45is4.4158 (In English)

Md. Mijanur Rahman, Ismat Ara Shama, Siamur Rahman and Rahmatullah Nabil (2022) "Hybrid Recommendation System to Solve Cold Start Problem". https://doi.org/10.5281/zenodo.7026121 (In English)

María Cora Urdaneta-Ponte, Amaia Mendez-Zorrilla and Ibon Oleagordia-Ruiz (2021) "Recommendation Systems for Education: Systematic Review". https://doi.org/10.3390/electronics10141611 (In English)

Pengyu Guo, Mohd Khalid Mohamad Nasir and Yishuai Xu (2024) "Collaborative Filtering Recommender System for Online Learning Resources with Integrated Dynamic Time Weighting and Trust Value Calculation". https://doi.org/10.18421/tem132-49 (In English)

Rui Zhou and Nan Zhang (2024) "Research on Recommendation Methods for Scientific and Technological Information and Their Application in College Education — Based on Knowledge Graphs". https://doi.org/10.2478/amns-2024-2832 (In English)

Shaina Raza, Mizanur Rahman, Safiullah Kamawal, Armin Toroghi, Ananya Raval, Farshad Navah and Amirmohammad Kazemeini (2024) "A Comprehensive Review of Recommender Systems: Transitioning from Theory to Practice". https://doi.org/10.48550/arXiv.2407.13699 (In English)

Yousef H. Alfaifi, (2024) "Recommender Systems Applications: Data Sources, Features, and Challenges". https://doi.org/10.3390/info15100660 (In English)

Yinping Ma, Rongbin Ouyang, Xinzheng Long, Zhitong Gao, Tianping Lai and Chun Fan (2023) "DORIS: Personalized Course Recommendation System Based on Deep Learning". https://doi.org/10.1371/journal.pone.0284687 (In English)

Zhang Xiong, Haoxuan Li, Zhuang Liu, Zhuofan Chen, Hao Zhou, Wenge Rong and Yuanxin Ouyang (2024) "A Review of Data Mining in Personalized Education: Current Trends and Future Prospects". https://doi.org/10.1007/s44366-024-0019-6 (In English)

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