A Systematic Review of Educational Recommender Systems: Techniques, Target Users, and Emerging Trends in Personalized Learning

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Abstract

This systematic review investigates the state of educational recommender systems (ERS) to synthesize trends, techniques, user focus, and research gaps in the domain. Guided by the PRISMA (Page et al., 2021) checklist, relevant studies were selected and analyzed based on key elements such as the recommendation techniques employed, target user groups, and application contexts. The thematic synthesis revealed that machine learning remains the most widely adopted approach, particularly classifiers, clustering, and ensemble methods. Collaborative filtering, hybrid models, and ontology-based approaches featured prominently, though techniques such as deep learning and genetic algorithms were underutilized despite their potential. Most systems primarily targeted students, with relatively limited attention given to educators, administrators, and lifelong learners. Application areas such as course selection, career guidance, curriculum development, and digital literacy support were observed. However, challenges such as limited inclusivity, contextual adaptability, and underrepresentation of workplace learners were noted. The findings underscore the need for more inclusive, scalable, and context-aware recommender systems. The review highlights opportunities for advancing digital literacy, helping users to navigate through digital tools, especially in the workplace and non-formal learning environments, and calls for future research to explore ethical, explainable, and cross-regionally deployable ERS frameworks. The study contributes a comprehensive synthesis that informs both the academic discourse and practical development of personalized, user-centered educational recommender systems.

Introduction

In an era where digital transformation continues to reshape educational landscapes, recommender systems (RS) have emerged as pivotal tools for enhancing personalized learning, improving decision-making, and supporting learners across various levels and contexts. While the use of these systems is gaining momentum, the current state of knowledge remains fragmented. Prior research has predominantly focused on student-centered applications, with comparatively limited attention given to educators, administrators, and lifelong learners (Bhatt et al., 2025). Furthermore, the diversity of techniques—ranging from collaborative filtering to emerging AI-based approaches—has resulted in varying levels of effectiveness, scalability, and contextual adaptability.

These uncertainties highlight the need for a consolidated understanding of the techniques employed, their application areas, and the gaps that persist. Although several reviews have examined recommendation systems in education, many have lacked systematic methodological rigor or have been limited to specific technical or user domains.

This review aims to systematically synthesize the existing body of literature to identify dominant patterns and emerging trends and assess the application context to which recommendation systems are being applied and the extent of personalization in educational systems. Given the rise of digital transformation across education and the workplace, this review also addresses the increasing importance of digital literacy and the potential of recommender systems to support lifelong learning and upskilling initiatives. By employing the PRISMA framework (Page et al., 2021), the review ensures rigorous and transparent synthesis, while aiming to inform the design and implementation of more context-aware and ethically sound recommender systems.

To guide the review, the following research questions (RQs) were formulated;

RQ1: Which recommendation techniques are most commonly used in the development of educational recommender systems?

RQ2: Who are the primary user groups, and what application contexts are most frequently addressed by these systems?

RQ3: What key trends and research gaps exist in the current application of recommender systems within the educational domain?

RQ4: In what ways can the synthesized insights from existing studies inform and shape future research directions in this field?

Methods

This systematic review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) to ensure transparency, reproducibility, and methodological rigor during the study selection and synthesis process. The review aimed to explore how recommender systems (RSs) are applied in educational settings, particularly their role in promoting digital upskilling. A comprehensive literature search was conducted using the Dimensions database (*Publications - Dimensions*, n.d.), targeting peer-reviewed journal articles published between 2016 and 2025. A total of 5,632 records were initially identified, from which 500 relevant articles were exported in .csv and .bib formats. The .bib file was imported into Rayyan (*Rayyan | Screening*, n.d.), a web-based tool designed to streamline the screening process for systematic reviews. Rayyan's duplicate detection feature confirmed that no duplicate entries were present.

Before screening, 378 records were automatically excluded within Rayyan: 376 were review or survey papers removed according to a predefined exclusion protocol, and two were excluded for being written in non-English. This exclusion was necessary to focus on original empirical studies offering direct insights into the development, implementation, and evaluation of RSs in educational contexts. Review papers were excluded as they typically summarize existing findings rather than introduce new evidence, potentially introducing bias or redundancy. Following the automation-based exclusions, 121 records remained for manual screening. Two reviewers independently screened titles and abstracts using Rayyan’s blind review feature, classifying articles as “Include”, “Maybe” or “Exclude.” Disagreements were resolved through discussion, and 26 articles were excluded at this stage due to lack of relevance.

The remaining 95 articles were imported into Zotero (*Zotero | Your Personal Research Assistant*, n.d.) for full-text evaluation. During this phase, 36 articles were excluded due to the unavailability of full-text access. This left 59 studies that met all inclusion criteria. For the final synthesis, these 59 articles underwent detailed data extraction using Microsoft Excel. Two reviewers collaborated in this process: one focused on identifying the target users and educational context, while the other examined the techniques or methods used in the implementation of RSs. This structured dual-review process helped ensure consistency, accuracy, and depth in synthesizing findings. An overview of the article selection process is presented in Figure *2* (PRISMA flow diagram).

Data Sources and Search Strategy

The literature for this review was sourced from the Dimensions database (*Publications - Dimensions*, n.d.), comprising peer-reviewed articles published in reputable academic outlets. The search strategy, as shown in Figure *1*, utilized a combination of keywords and Boolean operators—("recommendation system" OR "recommender system") and applied specific filters including publication years from 2016 to 2025, limiting results to articles, and focusing on research categories under “Education” and “Quality Education.” This approach ensured comprehensive and relevant coverage of diverse applications of recommendation systems within the educational domain. The search was conducted and data were retrieved on March 10, 2025.

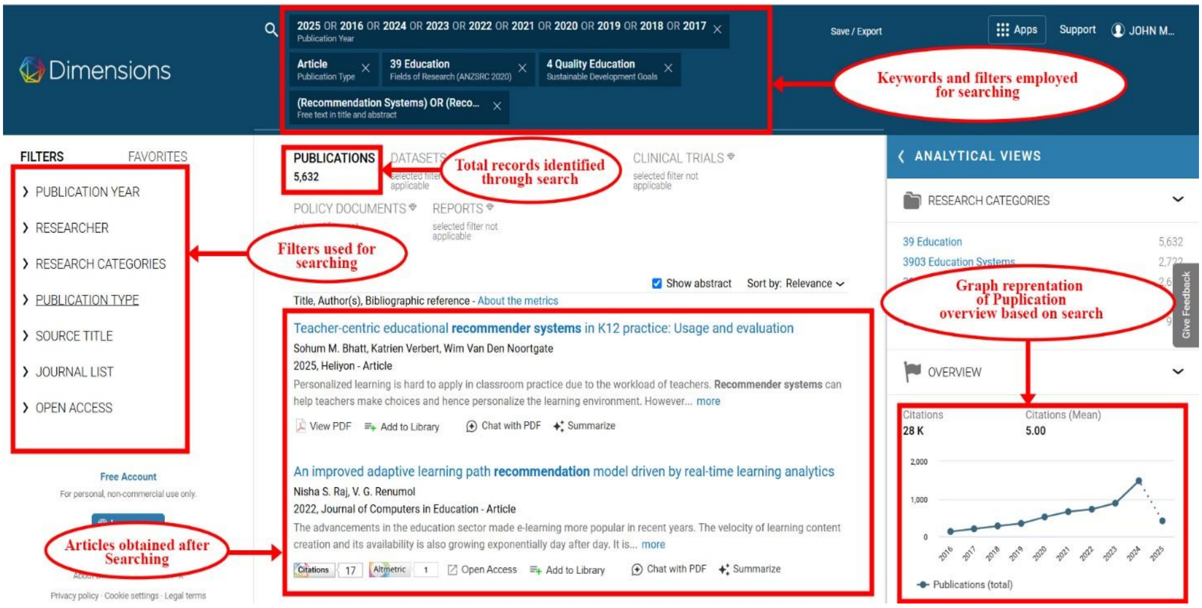


Figure 1. Screenshot of the Dimensions Database Search Results Showing Filtered Peer-reviewed Articles related to Recommendation Systems in Education, retrieved on March 10, 2025.

Inclusion (IC) and Exclusion Criteria (EC)

Inclusion Criteria

IC1. Studies that specifically explore or assess the use of recommendation systems in educational or learning contexts were included

IC2. Only articles with full-text availability were considered for inclusion

IC3. Publications were limited to peer-reviewed journal articles written in English

Exclusion Criteria

EC1. Studies focused solely on recommendations unrelated to educational context were excluded

EC2. Articles not written in English or those without full-text access were excluded

EC3. Review and survey papers were not considered for inclusion

Data Extraction and Analysis

Each of the 59 selected articles was thoroughly analyzed based on key dimensions, including the type of recommendation technique employed, the intended target users, and the specific educational context in which the system was applied. This data was systematically extracted by two independent reviewers using Microsoft Excel—one focusing on the recommendation techniques and methods, while the other examined the user groups and application settings. The extracted information was then thematically synthesized to uncover common patterns, emerging trends, research gaps, and prospective directions. The resulting insights were organized around key thematic areas such as personalization strategies, user-centered system design, recommendation system architecture, and approaches aimed at enhancing learner engagement.

Results

A total of 5,632 records were initially retrieved through comprehensive database searches. From these, the 500 most relevant records were exported for further assessment. Using Rayyan as the automation tool, 376 records were identified as ineligible and excluded, along with 2 non-English articles. This left 121 records for manual screening, of which 26 were excluded based on their titles and abstracts. The remaining 95 records were imported into Zotero for a full-text review, during which 36 were excluded due to lack of full-text availability. Finally, 59 studies met the inclusion criteria and were incorporated into the final review. The selection process followed PRISMA(Page et al., 2021) guidelines, as illustrated in Figure *2*.

Study Characteristics

This systematic literature review analyzed 59 primary studies published between 2016 and 2025. These studies implemented a diverse array of recommendation system techniques in educational contexts. The aim was to support personalized learning, career guidance, course selection, and institutional decision-making. The studies were sourced from peer-reviewed journals, covering global research in higher education, lifelong learning, K-12 environments, and vocational training. Table *1* summarizes the key attributes of the studies, including the techniques/Algorithms used and the context or target users.

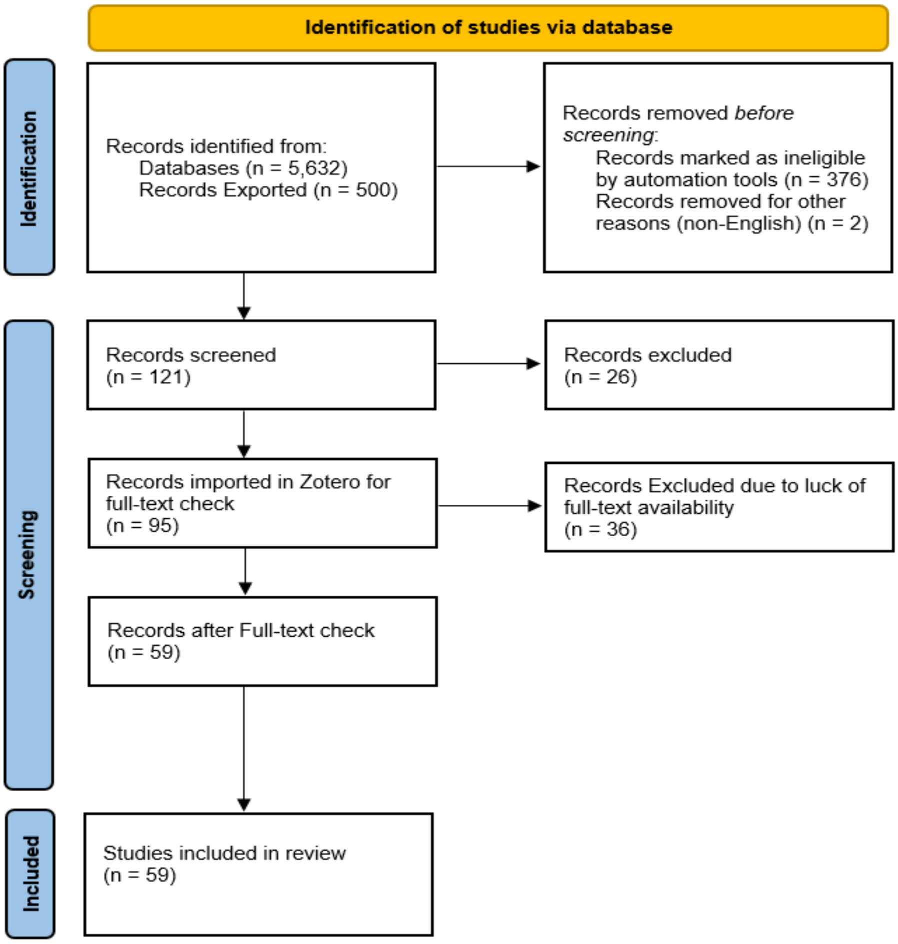


Figure 2. The PRISMA Flow Chart of the Study Selection Process

Table 1. Summary of Studies by Technique and Target Context

Article	Techniques/Algorithms Used	Target Users/Context
(MARÍN et al., 2016)	Multi-Agent System (MAS)	Students in the learning context for recommending appropriate educational resources
(Knez et al., 2017)	Group formation algorithms	Students and teachers for dividing students into homogeneous/heterogeneous groups for e-learning
(Atmadja, 2018)	Geolocation-based recommendation system	Students in the university selection context based on geographical location
(Bošnjak et al., 2018)	AI applications, expert and tutoring systems, knowledge discovery	Students in career guidance and counseling
(Palilingan & Batmetan, 2018)	Bayesian Method	Students for professional recommendation
(Natividad et al., 2019)	Fuzzy-based feature selection	Senior high school students and guidance counselors in career recommendation

Article	Techniques/Algorithms Used	Target Users/Context
(Kusumaningrum et al., 2017)	Association Rule Mining	Students in the subject selection context
(Y. Zheng, 2019)	Preference correction methods	Students, instructors, parents, and publishers in preference correction for educational recommendations
(Assami et al., 2020)	Ontological representation of learner models	Learners in the distance learning context
(Bulathwela et al., 2020)	Integrative Approach, Content Novelty Modeling	Lifelong learners
(Paytaren, 2020)	Collaborative Filtering (CF)	Faculty members in higher education institutions
(Gloerfeld et al., 2020)	Educational data mining, machine learning	Students for self-learning support
(Dhar & Jodder, 2020)	Machine learning algorithms, correlation-based feature selection	Students for program recommendation
(Borovyk, 2020)	Machine learning, data analysis techniques	Management in higher education institutions for decision making
(de Schipper et al., 2021)	Summative assessment data analysis, recommendation algorithms	Students for personalized feedback in assessments
(Mehta et al., 2021)	Problem analysis and system development planning	Prospective university students in the admissions process
(Mazhoud et al., 2021)	Learner profile modeling based on annotation activity	Students for assisting in learner activities
(Oktavia & Sujarwo, 2021)	Interactive recommender system using LinkedIn-based competency analysis	Higher education institutions seeking learning partners
(Shishehchi et al., 2021)	Ontology-based knowledge representation, Semantic rules	Learners in programming domain
(JothiLakshmi & Thangaraj, 2018)	Educational Data Mining algorithms	Educational institutions monitoring student performance
(Marras et al., 2021)	Fairness metric, post-processing approach	Learners
(SONGER & YAMAMOTO, 2021)	Post-project interviews	Learners for decision making in self-directed learning
(Dubas & Kunanets, 2021)	RIASEC Career Guidance Test, Individual Educational Trajectory Modeling	IT students for career guidance

Article	Techniques/Algorithms Used	Target Users/Context
(Baidada et al., 2021)	Hybrid Filtering	Learners
(Wardani et al., 2022)	Forward Chaining, SDLC	Students for major decision-making
(Bulathwela et al., 2022)	Hybrid recommender systems	Lifelong learners on educational platforms
(Saleh et al., 2023)	Naïve Bayes Classifier Algorithm	Teachers and learners for determining learning strategies
(Benabbes et al., 2023)	K-Means (ML)	Learners for retrieving learner characteristics
(Songer & Yamamoto, 2023)	Case-based analysis	Students supporting decision making
(Dai et al., 2023)	Explainable Recommender System (XRS)	Students for performance improvement through explanations
(Kaledin et al., 2023)	Collaborative Filtering (CF), Machine Learning	Students for predicting progress in elective disciplines
(Nanda, 2023)	ALBERT (Lite BERT), Deep Learning, NLP	Students for assessing learning outcomes
(Tyagi, 2019)	Machine Learning algorithms, Data Analysis	Students for suggesting colleges based on entrance exam ranks
(Timmi & Faculty of Sciences Dhar El Mehraz, 2024)	hybrid approach, incorporating both Content-Based Filtering (CBF) and Collaborative Filtering (CF) algorithms	Students in the context of learning through videos
(Qiao, 2024)	Convolutional Neural Network (CNN)	Students for online learning resources
(Wahyuliningtyas et al., 2024)	CF, Machine Learning	High school students for selecting web programming materials
(Kohlhase et al., 2024)	Machine Learning, Symbolic AI, Statistical AI	Students for advisory services and learning material selection
(Chanaa & El Faddouli, 2024)	Linked Open Data (LOD), Machine Learning	Students for course recommendations based on prerequisites
(Wu & Kang, 2024)	Joint Hidden Semantic Model (JHSM), CNN	Music teachers and students in modern music education
(Chen & Huang, 2024)	Deep Learning	Tourism Management Students
(Li et al., 2024)	CBOW & SVM Models	Higher Education Curriculum Design
(X. Liu, 2024)	Knowledge Graph Method	Online Learners
(Takii et al., 2024)	Information Retrieval	Japanese Junior High School Students Learning

Article	Techniques/Algorithms Used	Target Users/Context
	Technology	Foreign Language
(Delahoz-Domínguez & Hijón-Neira, 2024)	ML (Xboost, Random Forest, GLMNET, KNN)	Students selecting university degree programs
(Wong et al., 2024)	ML Techniques	Higher education students selecting Generic Competency Development Activities
(Wang et al., 2024)	Deep Learning	Vocational Education Students
(Raj & Sathiyan, 2024).	ML, Ontological Framework	Undergraduate Students, Lifelong Learners, Professionals
(Luo, 2024)	Hybrid Interest Model, Enhanced CF	Students in Media Education
(Chen & Huang, 2024)	Collaborative Filtering, Cluster Analysis	College Students for English Writing Instruction
(Zhu, 2024)	Collaborative Filtering, Multi-dimensional Data Fusion	Students and teachers involved in personalized or precision learning environments
(Ding, 2024)	Collaborative Filtering (CF), Clustering algorithms	University and college students, along with educators, pursue digital transformation in English education.
(Zhong et al., 2024)	Knowledge graph	Students in professional music courses, Online learners with specific skill levels and interests and Educators designing personalized music education content
(Bhatt et al., 2025)	User-centric evaluation	Teachers implementing personalized learning
(Arcinas et al., 2025)	Principal Component Analysis (PCA) for feature selection, AdaBoost, K-Nearest Neighbor (KNN), Naïve Bayes for classification	Higher education students for course recommendation
(Yu et al., 2025)	ML, Small-scale knowledge graph	Vocational teachers to improve teaching; students get personalized content to boost learning.
(Pinos Ullauri et al., 2025)	Psychometric modeling with genetic algorithm framework	Higher education students aiming to develop soft skills
(Chai, 2025)	Collaborative filtering, Genetic algorithms, K-means clustering	College students in innovation and entrepreneurship education
(L. Zheng et al., 2025)	Ontological reasoning, Similarity fusion calculation	College students in physical education courses
(Lahiassi et al., 2025)	Data-Driven techniues	Master's students in collaborative learning

Article	Techniques/Algorithms Used	Target Users/Context
		environments

Techniques and Algorithms Employed

The analysis reveals that Machine Learning techniques were the most widely adopted, appearing in over 20 (Akash Cherukuri, 2019; Arcinas et al., 2025; Bourahmoune et al., 2022; Dhar & Jodder, 2020) studies and encompassing classifiers, clustering (K-means), and ensemble methods (e.g., AdaBoost, XGBoost). Collaborative Filtering followed, used in more than 10 studies (Guo, 2024; Kaledin et al., 2023, 2023), either standalone or within hybrid systems. Ontology-based models and knowledge graphs were used in 8 studies (N. Liu, 2023; Shishehchi et al., 2021; Zhong et al., 2024), reflecting their growing role in personalization. Hybrid approaches, combining CF, content-based filtering, and semantic methods, aimed to improve accuracy and relevance (Baidada et al., 2021). Less common yet impactful techniques included Fuzzy Logic, Genetic Algorithms, Deep Learning, and Semantic Web, applied for enhanced adaptability and decision-making. The Table *2* and corresponding graph Figure *3* highlight the distribution of techniques, with Machine Learning and Collaborative Filtering standing out as the most frequently used methods. Other techniques, such as Hybrid Approaches, Ontology-based Methods, and Deep Learning, show a targeted application, emphasizing their specific role in educational recommender systems.

Table 2. The Most Frequently Used Approaches in the Selected Studies

Technique/Approach	Frequency	Example Studies
Machine Learning (General)	25	(Akash Cherukuri, 2019; Arcinas et al., 2025; Dhar & Jodder, 2020) etc.
Collaborative Filtering (CF)	12	[36], [65] etc.
Hybrid Approaches (CBF + CF, etc.)	10	(Baidada et al., 2021; Luo, 2024) etc.
Ontology-based Methods	8	(Raj & Sathiyan, 2024; Shishehchi et al., 2021) etc.
Deep Learning	6	(Tang, 2023; Wang et al., 2024) etc.
Data Mining Techniques	5	[12], [46] etc.
Knowledge Graphs	4	(N. Liu, 2023; Zhong et al., 2024) etc.
Genetic Algorithms	3	(Bhatt et al., 2023; Chai, 2025)etc.
Fuzzy Logic / Bayesian Models	2	(Natividad et al., 2019; Palilingan & Batmetan, 2018)

Figure 3 illustrates the distribution of key techniques identified across the reviewed studies. Machine Learning methods appeared most frequently, followed by Collaborative Filtering, Hybrid Approaches, and Ontology-based methods, indicating a strong focus on intelligent and personalized recommendation strategies.

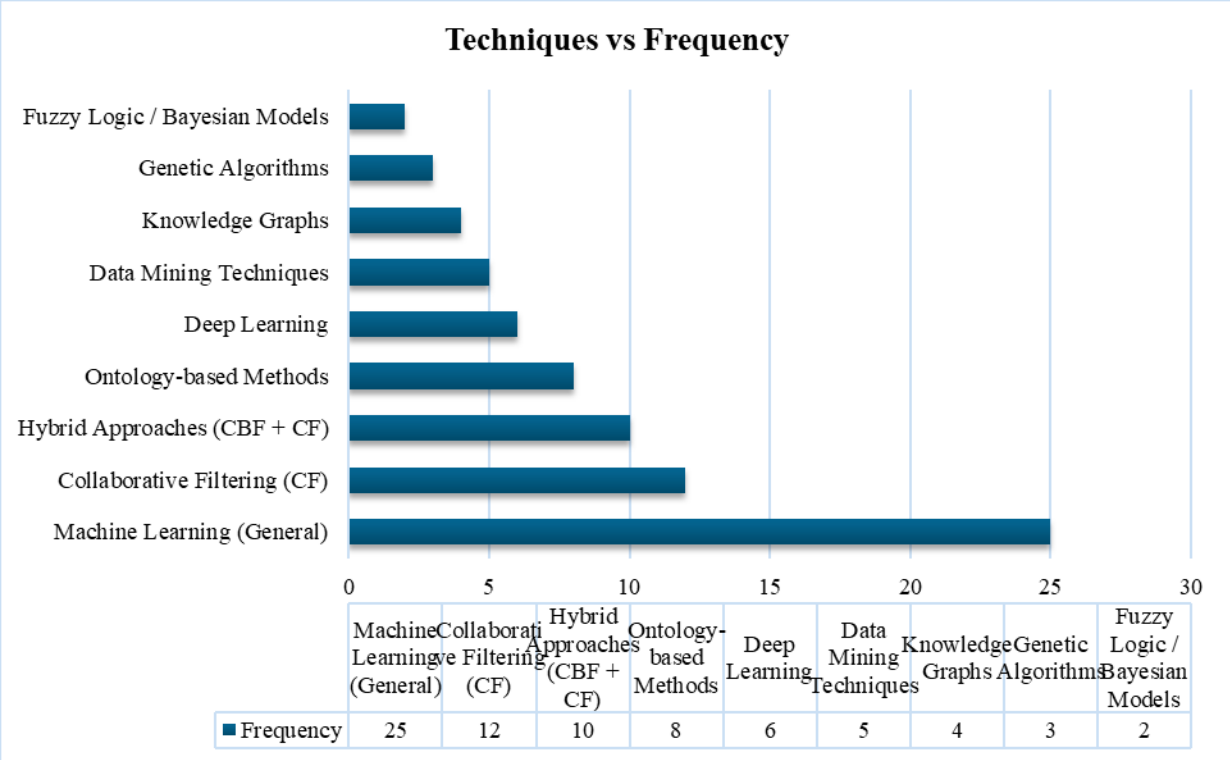


Figure 3. Frequency of Techniques and Approaches Used in Educational Recommender Systems

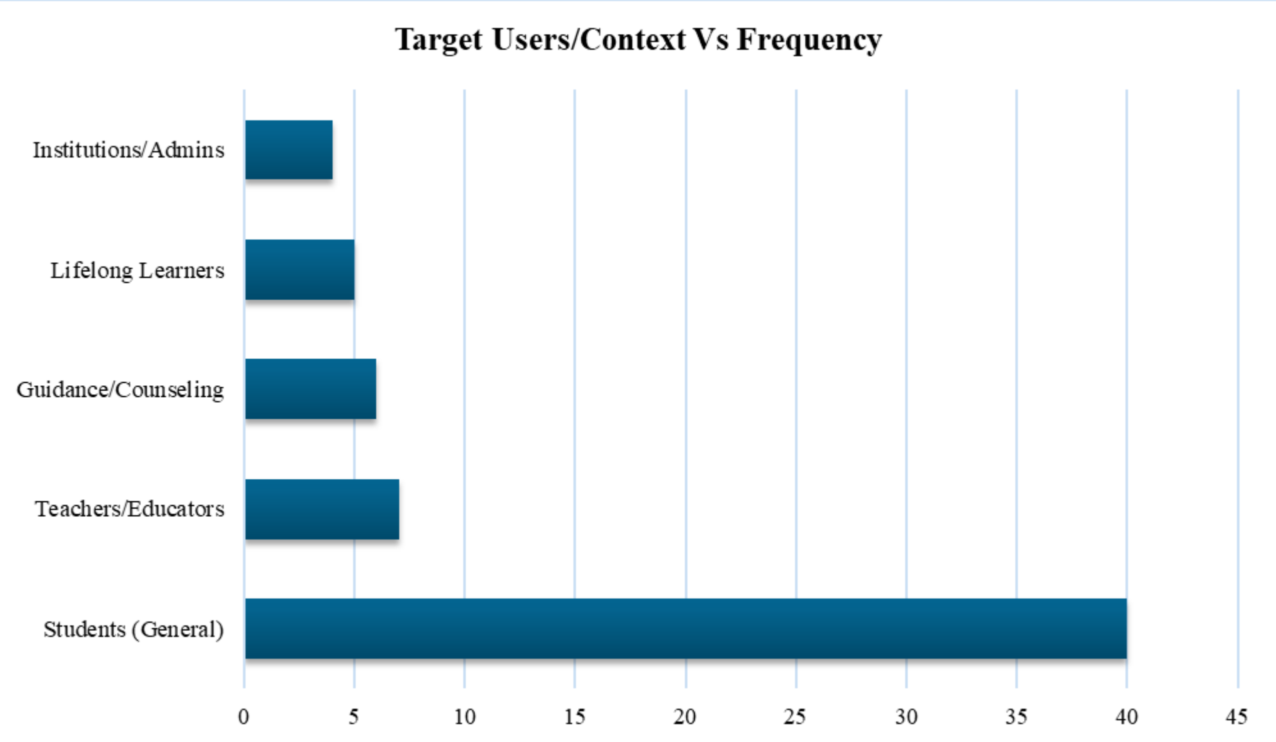
Target Users and Educational Contexts

The reviewed studies targeted a wide range of educational actors, with students being the primary focus, from high school to university levels (Delahoz-Domínguez & Hijón-Neira, 2024; Knez et al., 2017). Lifelong learners have gained attention in recent studies, reflecting the increasing emphasis on continuous, non-formal education (Bulathwela et al., 2020). Teachers and educators were also targeted, especially in studies supporting content delivery and pedagogical decisions (Dubas & Kunanets, 2021; Paytaren, 2020). A few studies addressed institutional decision-making, such as curriculum design, admissions, or performance monitoring (Borovyk, 2020). Common application contexts included career guidance, course or subject selection, curriculum development, learning strategy recommendations, and content personalization(Natividad et al., 2019). The targeted user groups can be categorized as presented in the Table 3.

Table 3. Classification of Targeted User Groups in the Reviewed Studies

Target User/Context	Frequency	Sample Studies
Students (General)	40	(Chai, 2025; Raj & Sathiyan, 2024; Wahyuliningtyas et al., 2024) etc.
Teachers/Educators	7	(Yu et al., 2025; L. Zheng et al., 2025) etc.
Guidance/Counseling	6	(Borovyk, 2020; Roy, 2024) etc.
Lifelong Learners	5	(Bulathwela et al., 2020; Raj & Sathiyan, 2024) etc.
Institutions/Admins	4	(Borovyk, 2020; Paytaren, 2020) etc.

The following graph Figure 4 visualizes the distribution of targeted user groups across the reviewed studies. It highlights the frequency of each user group in relation to the studies analyzed.



	Students (General)	Teachers/Educators	Guidance/Counseling	Lifelong Learners	Institutions/Admins
Frequency	40	7	6	5	4

Figure 4. Distribution of Target User Groups and Their Frequency in the Reviewed Studies

Temporal and Thematic Trends

The analysis uncovered both temporal and thematic trends in the evolution of educational recommender systems. Over the years, there has been a clear progression from basic rule-based and collaborative filtering techniques toward more sophisticated approaches, including machine learning, hybrid models, deep learning, and ontology-driven frameworks(Shishehchi et al., 2021). Thematically, earlier studies predominantly addressed simple personalization tasks such as resource recommendations (MARÍN et al., 2016). In contrast, more recent research has shifted focus toward adaptive learning environments, career pathway recommendations, and lifelong learning support(Raj & Sathiyan, 2024). Additionally, the adoption of deep learning (Tang, 2023), knowledge graphs(Zhong et al., 2024) , and explainable AI reflects an increasing emphasis on system transparency, interpretability, and building user trust. These developments mirror the dynamic technological landscape and the evolving expectations of diverse educational stakeholders.

This growth trajectory is also evident in the volume of academic output over time. As illustrated in Figure 5, the number of publications related to educational recommender systems has consistently increased from 2016 to 2024, peaking sharply in 2024. The notable drop in 2025 can be attributed to incomplete indexing for the current year at the time of data extraction (April 2025). This upward trend underscores the rising academic and practical interest in the field, driven by both innovation in AI technologies and the pressing need for personalized educational support.

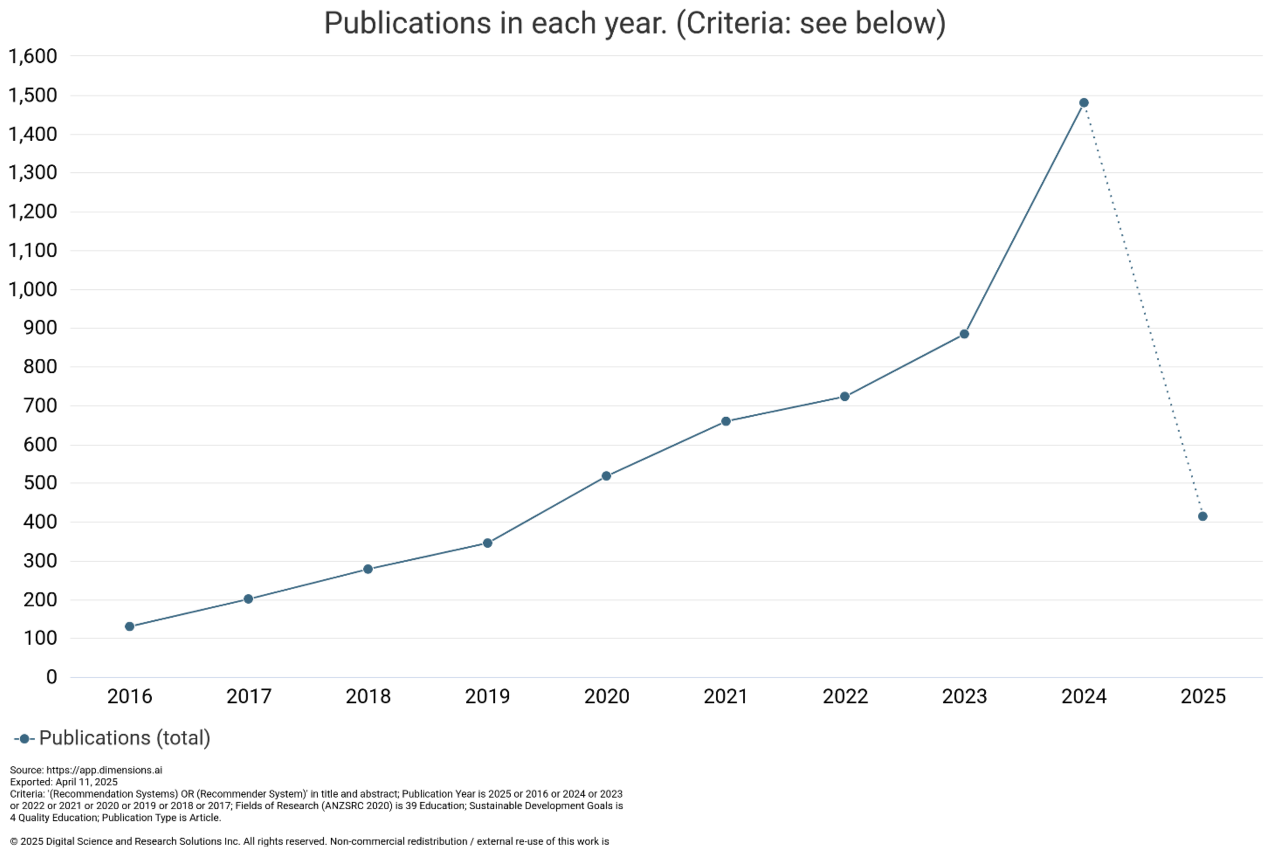


Figure 5. Annual Publication Trends in Educational Recommender Systems from 2016 to 2025

Discussion

This section presents a critical interpretation of the findings in relation to existing literature, identifying prevailing patterns, gaps, and emerging directions in the field of educational recommender systems. It also addresses the limitations of the study, and the broader implications for practice, policy, and future research.

Synthesis and Interpretation of Key Findings

The findings of this review reveal that Machine Learning (ML) techniques, particularly classifiers, clustering, and ensemble methods, are the most commonly employed approaches in educational recommender systems, echoing broader trends observed in the existing literature. Collaborative Filtering (CF) and hybrid models also feature prominently, aligning with prior research and highlighting their ability to improve personalization. Ontology-based methods and knowledge graphs are popular, particularly in systems emphasizing semantic understanding and learner context. However, most implementations remain focused on students, reflecting a continuation of past research priorities but leaving other potential user groups underexplored. Compared to previous reviews, this study also notes an emerging interest in applying recommender systems for lifelong learning and digital literacy, showing evolving research directions.

Limitations of the Study

Despite applying a systematic and rigorous PRISMA-based approach, the review process has several limitations. The search was limited to English-language publications and relied solely on one database (*Publications - Dimensions*, n.d.), which may have excluded relevant studies available in other databases such as Scopus, Web of Science, or Google Scholar. These additional sources could have broadened the scope by capturing diverse perspectives. While thematic synthesis enabled the identification of recurring patterns, some contextual nuances might have been overlooked during categorization. Moreover, given the rapid advancement of AI and educational technologies, some recent or in-press studies may not have been captured if they were not yet indexed. These limitations could affect the comprehensiveness and representativeness of the review findings.

Recommendations and Future Research

The findings underscore the need for recommender systems that are more inclusive, scalable, and context-aware. For practice, developers should focus on expanding the user base beyond students to include educators, administrators, lifelong learners, and working professionals. Policies should support the integration of adaptive and personalized technologies across various education levels and workplace environments, especially in underrepresented regions. Importantly, as digital technologies permeate nearly all aspects of modern life, there is a growing need to explore how recommender systems can support digital literacy and upskilling—helping individuals navigate digital tools effectively in both learning and workplace contexts. For research, there is a clear call to investigate underutilized techniques such as deep learning and genetic algorithms, assess the long-term impact of recommendation systems, and design ethical, transparent, and explainable frameworks. Cross-regional collaboration and real-world piloting will be essential to driving forward inclusive and effective educational recommender systems that support lifelong learning and digital empowerment.

Conclusion

This review has explored the landscape of educational recommender systems through a systematic analysis of recent studies, revealing a strong preference for machine learning techniques and collaborative filtering, with growing interest in hybrid and ontology-based models. While most systems target students, there remains a noticeable gap in serving other stakeholders like educators, lifelong learners, and institutional decision-makers. The findings point to a need for more inclusive, context-aware, and digitally adaptive systems that go beyond academic support to assist with digital literacy and workplace navigation. Despite following a rigorous PRISMA-based methodology, the review was limited by its reliance on a single database and English-only publications, which may have excluded valuable insights from other regions and languages. Furthermore, the rapid pace of technological advancement poses a risk of overlooking very recent, unindexed studies. The study emphasizes the importance of diversifying algorithmic techniques, enhancing personalization frameworks, and addressing ethical and explainability concerns. Future research should explore underutilized methods like deep learning and genetic algorithms, foster cross-regional collaboration, and pilot real-world implementations, especially in low-resource contexts. Policymakers and practitioners are urged to support the integration of recommender systems in a way that promotes equitable access, digital skills development, and lifelong learning opportunities

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