Revisión de estudios sobre análisis de los algoritmos de recomendación para plataformas educativas orientados a la recomendación de recursos didácticos.

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Resumen

Las plataformas educativas se han convertido en herramientas digitales útiles y dinámicas dentro de las instituciones educativas. Este estudio tiene como objetivo analizar los algoritmos de recomendación utilizados en plataformas educativas, se revisaron 317 estudios y seleccionaron 73 relevantes mediante una metodología sistemática en tres fases: (a) planificación donde se definieron las preguntas sobre la implementación de algoritmos de recomendación; (b) ejecución mediante una búsqueda sistemática de artículos en diversas bases de datos; y (c) análisis evaluando las publicaciones seleccionadas. Los hallazgos indican que los algoritmos de recomendación son fundamentales para la personalización de contenidos educativos. Se clasifican en filtrado colaborativo, filtrado basado en contenido, sistemas híbridos, filtrado demográfico y sistemas basados en conocimiento. Las plataformas que integran estos algoritmos potencian la eficacia del aprendizaje, ayudando a los usuarios a descubrir contenido relevante y adaptado a sus necesidades. La inteligencia artificial se considera en este estudio como una tecnología habilitadora que permite la personalización del aprendizaje, más que como una variable de investigación. Por ello, se destaca la importancia de considerar la diversidad de estilos de aprendizaje y la privacidad de los datos en su implementación. Finalmente, la combinación de algoritmos de recomendación y plataformas educativas tiene un gran potencial para transformar la educación, siempre que se garantice que los usuarios mantengan el control sobre sus datos. De los artículos seleccionados, 15 estudios reportan implementaciones concretas de algoritmos: 40% corresponden a enfoques de deep learning, 20% a filtrado colaborativo, 20% a sistemas híbridos, 13% a sistemas basados en conocimiento y 7% a filtrado demográfico, lo que evidencia una adopción aún limitada de estas últimas aproximaciones.

Palabras clave: Plataformas educativas, Algoritmos de recomendación, Inteligencia artificial en educación.

Review of Studies on Analysis of Recommendation Algorithms for Educational Platforms on Didactic Resources

ABSTRACT

Educational platforms have become dynamic and valuable digital tools within academic institutions. This study aims to critically analyze the recommendation algorithms employed in educational platforms. A total of 317 studies were reviewed, of which 73 were selected through a systematic methodology comprising three phases: (a) planning, where research questions regarding the implementation of recommendation algorithms were defined; (b) execution, involving a systematic search of articles across various databases; and (c) analysis, evaluating the selected publications. The findings indicate that recommendation algorithms are essential for the personalization of educational content. These algorithms are categorized into collaborative filtering, content-based filtering, hybrid systems, demographic filtering, and knowledge-based systems. Platforms that integrate these algorithms enhance learning effectiveness by helping users discover relevant and tailored content. In this study, artificial intelligence is considered an enabling technology that facilitates personalized learning, rather than a research variable. Accordingly, the importance of addressing learner diversity and data privacy in the implementation of these systems is emphasized. Ultimately, the integration of recommendation algorithms and educational platforms holds significant potential to transform education, if personalization ensures users retain control over their data. Among the selected articles, 15 studies report concrete algorithmic implementations: 40% involve deep learning approaches, 20% collaborative filtering, 20% hybrid systems, 13% knowledge-based systems, and 7% demographic filtering—highlighting the limited adoption of the latter categories.

Keywords: Educational Platforms; Recommendation Algorithms; Artificial Intelligence in Education.

1. Introduction

Over the years, society in the educational field is constantly changing, students have become more independent in the learning process, in which personalized content is created (Rocamora & Salvador, 2022). Adaptive learning (AA) is a methodology used by New Information Technologies (NTIC), a system based on Intelligent Adaptive Learning (AAI) and data analysis reflected in digital platforms as essential tools, these systems could dynamically and automatically adapt the behavior, requirements and needs of the user through recommendation algorithms (RA) based on Artificial Intelligence (AI) (Pérez et al., 2024).

Through Learning Management Systems (LMS), RA allow monitoring of student learning, with tools to carry out activities such as forums, chats, videoconferences, discussion groups and have access to support resources such as articles, documents, PDF, slides, videos among others (Vargas Murillo & Vargas, 2021). They also allow information to be collected and analyzed for a long time, through configuration and algorithm results, these can indicate the strengths, weaknesses, and skills of the students, where the teacher can encourage, reinforce and adapt knowledge based on to these results (Quilla et al., 2021).

On the other hand, it is appropriate to analyze whether the use of LMS platforms contributes to the meaningful learning of students (Gracia et al., 2024). Using data mining, through AI algorithms within the education arena, it has evidenced the potential of the large volume of data stored in these systems (Sancán & Felipe, 2022). Currently, LMS are used by educational institutions for the implementation of virtual courses. An example is Moodle, which provides various resources and activities that interact with students and teachers, providing certain statistics and reports (Sigua et al., 2020). The alternative for the appropriate use of this tool is to implement big data on this platform, which develops new methods of exploring information from educational environments to know the way in which students learn to make informed decisions that maximizes the probability of a successful educational process (Bonami et al., 2020).

Research on the use of AI in education has gained relevance due to the emergence of immersive learning environments, where the recommendation of teaching resources relies on the development of advanced algorithms and technologies. In this context, AI is approached not as a research variable, but as an enabling technology that facilitates adaptive and personalized learning. This study aims to analyze recent literature on the implementation and management of recommendation algorithms within educational platforms. To achieve this, a systematic methodology was applied, involving exhaustive study selection processes and the formulation of research questions that guide a focused exploration of AI-driven recommendation techniques for educational resources.

Although there have been scattered advances in the use of recommendation algorithms in educational platforms, previous reviews have mainly focused on (a) general technical taxonomies or (b) descriptions of virtual environments without integrating comparative evidence on pedagogical impact. A lack of systematization persists that links families of algorithms with reported educational metrics and methodological gaps. Therefore, this study aims to critically analyze recent literature of the 2019–2024 on AR oriented toward educational resources in learning platforms, classifying technical approaches and evaluating their contributions and shortcomings. Three research questions are formulated RQ1: innovations and emerging approaches, RQ2: predominant implementations and methods, and RQ3: attributed impact on personalization and learning. This framework guides the systematic methodology detailed in the following section.

2. Methology

This study follows a systematic review process (Kitchenham, 2004) and is carried out through the following phases: planning, implementation, and analysis.

2.1. Planning phase

Through the proposed methodology, the research questions are presented with the aim of giving a more direct approach to the literary review.

- RQ1: What are the innovative proposals and approaches that can be developed through recommendation algorithms in teaching within educational environments?
- RQ2. What are the most effective implementations of RA methods applied in education?
- RQ3. What is the impact of educational platforms that use recommendation systems for educational resources?

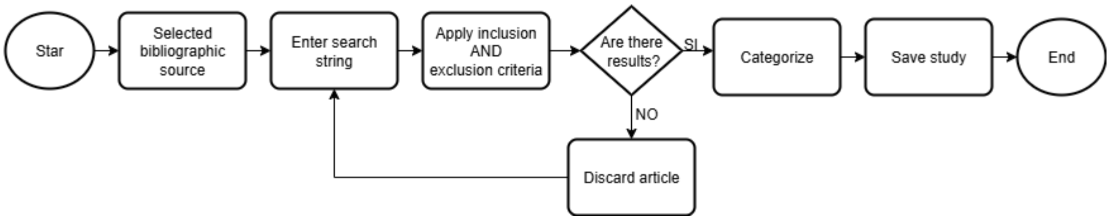
A systematic search of scientific articles and journal publications was conducted, restricted to literature published within the last six years. To this end, the following databases and repositories were consulted: IEEE Xplore, ScienceDirect, Dialnet, IOP Science, BASE, MDPI, arXiv, Springer, Web of Science, and DOAJ. The search strategy was operationalized through query strings combining the following keywords: “recommendation algorithms,” “content managers,” “adaptive learning,” “educational platforms,” “implementation,” and “artificial intelligence.”

The study applied predefined inclusion and exclusion criteria to ensure the rigor and relevance of the corpus. Inclusion criteria encompassed peer-reviewed journal articles addressing recommendation algorithms in virtual environments; studies on research-oriented and educational platform tools; articles on learning management systems; investigations related to the optimization of teaching resources; and research on the implementation of virtual learning platforms. Exclusion criteria involved the removal of articles published more than five years prior to the search window, as well as publications written in languages other than English or Spanish.

2.2. Implementation phase

The objective of this phase is to systematically address the research questions by conducting a thorough search for primary studies that substantiate the validity of the information. Figure. 1 illustrates the process of study selection as outlined in the search protocol.

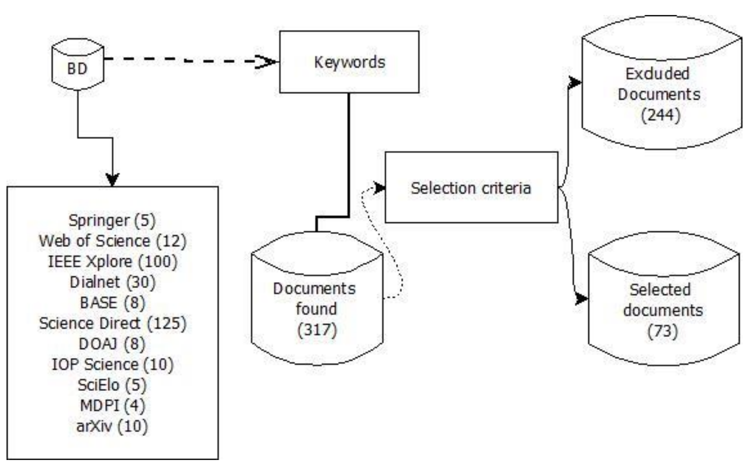
2.2.1. Figure. 1. Article selection process.



Source: Authors 2026.

In this study, a total of 73 articles published between 2019 and 2024 were selected. These articles are presented as the results of the search, aligned with the research questions formulated and filtered according to the established inclusion criteria. The results are categorized by year, the databases from which they were sourced, and the findings of each study, showing their contributions to this research. A summary of the selected articles is illustrated in Figure 2.

2.2.2. Figure 2. Articles selected through the different processes applied.



Source: Authors 2026.

2.3. Analysis phase

A total of 317 scientific publications were obtained, which were evaluated for the study analysis. As a result of this process, 73 relevant articles were selected. Based on these results, the research was categorized, discussions and conclusions were formulated regarding RA for educational resources.

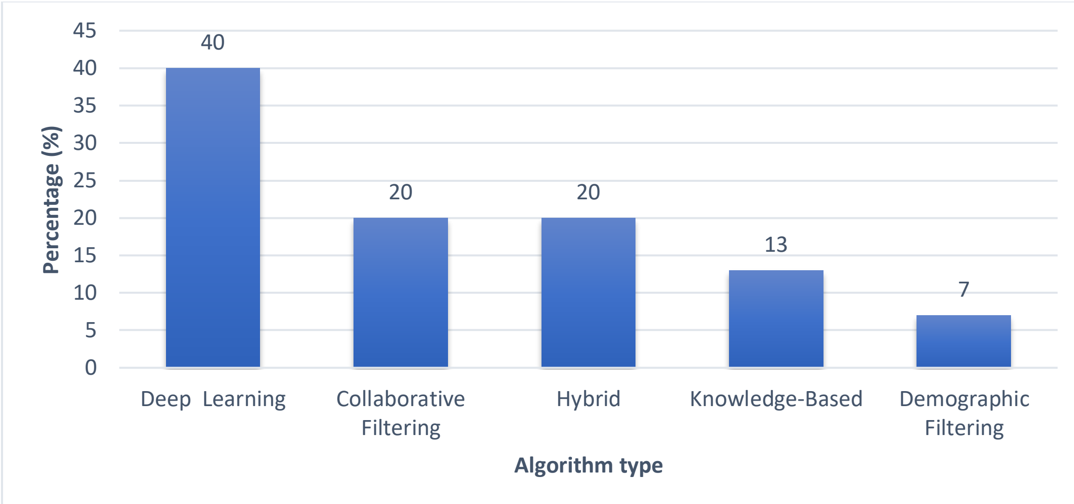
It is essential to recognize that the systematic review of the selected articles emphasizes themes related to the variables of the research questions, aimed at improving educational quality through learning techniques and RA in conjunction with AI. Among the highlighted algorithms are collaborative filtering (Yan, 2024), content-based recommendation (Isinkaye et al., 2024), and hybrid recommendation systems (Sivasankari & Dhilipan, 2024). Furthermore, RA are classified into collaborative filtering, which is subdivided into user-based and item-based; content-based recommendation; hybrid systems; demographic filtering; and knowledge-based filtering.

Overall, the methodology ensured a systematic and reproducible process: searches were conducted across ten multi-disciplinary and specialized databases, duplicates were removed using Parsifal, two reviewers independently applied the inclusion and exclusion criteria, and technical variables for algorithm families and pedagogical/platform variables platform type were extracted.

3. Results

This section addresses research questions, demonstrating that the use of technologies, such as RA, can optimize both cognitive performance and students' ability to self-regulate learning. It analyzes how research and proposals on these algorithms can facilitate the implementation of effective methods in educational platforms. These findings not only reflect technical trends but also offer valuable insights into how RA can enhance student autonomy, cognitive engagement, and the personalization of learning pathways. These findings are visually summarized in Figure 3.

3.1. Figure 3. Distribution of algorithm types implemented in selected studies.



Source: Authors 2026.

The following Table 1. summarizes key types of recommendation algorithms used in educational platforms, highlighting their pedagogical advantages and limitations

3.2. Table 1. Summary of algorithmic approaches and their educational impact.

Algorithm Type	Educational Advantages	Limitations
Deep Learning	Highly adaptive to complex learning patterns; enables personalized content delivery based on user behavior and preferences.	Requires large datasets and computational resources; may lack transparency in decision-making.
Collaborative Filtering	Promotes peer-based recommendations; enhances engagement through shared learning experiences.	Dependent on user interaction data; suffers from cold-start problems for new users or items.
Hybrid	Combines strengths of multiple algorithms; improves accuracy and personalization.	Complex to implement and maintain; may require integration of diverse data sources.
Knowledge-Based	Provides recommendations based on expert-defined rules and domain knowledge; suitable for structured learning paths.	Limited adaptability to user behavior; requires manual knowledge engineering.
Demographic Filtering	Personalizes content based on user attributes such as age, location, or background.	May oversimplify learner needs; risks stereotyping and lacks behavioral nuance.

Source: Authors 2026.

RQ1: What are the innovative proposals and approaches that can be developed through recommendation algorithms in teaching within educational environments?

RA are key tools in the personalization of educational content, enabling students to access resources that align with their interests and skill levels. Several studies have explored the implementation of RA in educational settings, highlighting their potential to enhance the learning experience. For instance, (Javed et al., 2021) emphasizes the use of content-based algorithms on educational platforms in Australia, suggesting that these systems can improve information retention. However, there is a lack of diversity in the methodologies used, as many studies focus on a single type of approach, overlooking hybrid alternatives that could yield more effective results.

On the other hand, (Cao et al., 2019) proposes a model that combines knowledge graph learning and RA in Singapore, enabling a better understanding of user preferences and the provision of more relevant resources. Despite these advances, the lack of cultural contextualization in research is also evident, as effective personalization requires considering not only demographic data but also cultural and contextual factors that influence learning preferences. These limitations highlight the need to develop more comprehensive models that incorporate methodological diversity and cultural sensitivity to optimize the relevance of recommendations in diverse educational contexts.

In Mexico, the application of similarity metrics in collaborative filtering systems has been explored, demonstrating how these can optimize recommendations based on interactions among students, fostering a more collaborative learning environment (Olguín et al., 2019). Likewise, recommendation systems have been investigated to support decision making, suggesting that content-based systems can help students select materials that maximize their learning (Fonseca & Cornelio, 2022). In India, thematic models have been implemented alongside browsing history to create hybrid recommendation systems, allowing students to receive more precise and personalized recommendations (Rajendran & Sundarraj, 2021).

Additionally, optimizing human-machine interaction emerges as a key opportunity, as understanding how students interact with educational platforms allows for the design of more intuitive interfaces that facilitate learning and in-crease the effectiveness of recommendations. It is also fundamental to conduct long-term evaluations to measure not only immediate satisfaction but also the impact of recommendations on academic performance and the development of students' skills.

A study in the United Kingdom analyzed the impact of demographic factors on the acceptability of low-emission zones, using a demographic filtering approach (Player et al., 2023). Although this study is not directly related to education, its methodology can be adapted to better understand student preferences. For example, by applying demographic filtering in educational platforms, resource recommendations could be personalized based on characteristics such as age, gender, and geographic location of the students. This could result in increased academic satisfaction and improved grades, as students would receive more relevant materials tailored to their specific needs.

RQ2. What are the implementations of recommendation algorithms applied in education?

The implementation of RA in educational settings has shown great potential for personalizing the learning experience, although its effectiveness varies depending on the context and the type of algorithm used. According to (Zheng et al., 2020), using collaborative filtering have proven effective in enhancing student engagement by offering content tailored to their interests and previous behaviors. However, this approach can be limited in contexts where user data is scarce or where student diversity is high.

On the other hand, the study by (Channarong et al., 2022) emphasizes the importance of content-based algorithms, which can complement collaborative filtering by providing more precise recommendations based on the characteristics of educational materials and the individual preferences of students. The combination of both approaches, as suggested in (Sivasankari & Dhilipan, 2024) can maximize the relevance of recommendations and improve learning outcomes, indicating that hybrid implementations are a promising strategy in education.

Furthermore, (Liu et al., 2019) highlights that the interaction between students and RA is a critical factor influencing the effectiveness of these implementations. Platforms that allow active user feedback tend to offer recommendations more closely aligned with students' needs, thereby increasing satisfaction and academic performance. This finding underscores the need to design systems that not only use advanced algorithms but also encourage active student participation in their learning process.

However, as mentioned in (Samin & Azim, 2019), many studies focus on short-term results, which limits the under-standing of the long-term impact of these systems. For implementations to be truly effective, it is necessary to con-duct research that evaluates how RA affects learning and skill development over time.

RA have been implemented in various educational platforms, using approaches such as collaborative filtering, which is based on users' previous ratings and behaviors to suggest relevant content (Wu et al., 2020). These platforms, by recording students' interactions with educational resources, can dynamically adjust recommendations, thereby im-proving the quality of learning (Sologuren Insúa et al., 2019). However, it is crucial that these implementations con-sider the diversity of learning styles and educational contexts to avoid biases and ensure that all students benefit equitably (Ridzuan & Zainon, 2024).

RQ3. What is the impact of educational platforms that use recommendation systems for educational resources?

RA offers diverse proposals and innovative approaches to improving teaching in educational environments. The optimization of human-machine interaction emerges as a key opportunity; by understanding how students interact with educational platforms, more intuitive interfaces can be designed to facilitate learning and increase the effective-ness of recommendations. Additionally, it is necessary to conduct long-term outcome evaluations, as this will not only allow for measuring immediate satisfaction but also provide insights into how recommendations impact students' academic performance and skill development over time. The consideration of ethics and privacy in data usage is fundamental to the development of these systems. As algorithms become more sophisticated, it is essential to establish practices that ensure the protection of students' personal information, guaranteeing that data is used responsibly and effectively to personalize the educational experience (Wu et al., 2020).

Educational platforms that integrate RA have transformed the personalization and effectiveness of learning. Recent research highlights that RA enables these platforms to employ advanced computational techniques to suggest educational resources tailored to users' preferences and prior behaviors. This capability not only improves the overall user experience but also facilitates the discovery of relevant content, enriching the educational process and fostering a more dynamic and engaging learning environment (Bonami et al., 2020).

The core functionality of RA lies in the collection and analysis of user data, which allows these systems to make informed predictions about the resources most beneficial for everyone. This personalized approach has been shown to increase student satisfaction and improve academic performance, as students gain access to materials that closely align with their specific interests and needs (Oubalahcen et al., 2023). By adapting content delivery to individual learning patterns, RA contributes to creating a more student-centered educational experience.

To achieve optimal performance, it is essential that the algorithms driving these systems are meticulously trained and implemented using a variety of recommendation techniques. Some of the most common methods include decision trees (Loreti & Visani, 2024), neural networks (Ha & Chen, 2021), Naive Bayes classifiers (Juliani & Maciel, 2024), fuzzy logic (Zhang, 2023), natural language processing (NLP) (Gonzalez & Patel, 2019), affinity clustering algorithms (Bi et al., 2020) and the Apriori algorithm (Xie et al., 2020). The diversity of these techniques allows platforms to address different aspects of user behavior and learning preferences, leading to more accurate and effective recommendations.

Beyond personalization, RA in educational platforms have the potential to optimize academic outcomes and improve user satisfaction. When properly implemented, they enhance resource accessibility while fostering a more active and engaged learning process. For instance, RA can help students identify areas for improvement, prioritize their study time effectively, and access specific resources, all of which contribute to better academic performance (Yan, 2024).

Furthermore, the integration of AI in education has opened new possibilities for innovation. By leveraging deep learning techniques, RA can identify complex learning patterns and provide highly personalized educational re-sources tailored to each student's unique needs (Al Ka'bi, 2023). This level of personalization supports a more dynamic and adaptive learning environment, empowering students to take control of their educational process.

The personalization of educational platforms not only enhances cognitive performance but also facilitates informed decision-making in the learning process. The integration of RA into educational platforms allows students to select study materials that align with their preferences and objectives. Furthermore, collaborative filtering methods promote group learning by enabling the sharing of resources and recommendations based on interactions and prior experiences. The diversity of approaches and algorithms applied in different educational contexts provides a valuable comparative framework for future research and development.

The implementation of these technologies represents progress toward educational innovation, where technology be-comes a key ally in enhancing the effectiveness of learning and teaching. The impact of educational platforms with RA offers benefits in personalizing learning and optimizing teaching. However, to maximize these benefits, it is essential to address limitations related to data quality, student diversity, system interaction, and ethical concerns. Doing so will further improve the effectiveness of these platforms in the educational process. Educational platforms with RA not only personalize learning but also have the potential to optimize academic performance and increase user satisfaction. Proper implementation of these techniques is essential to overcome the challenges of the educational environment and transform the learning experience, making it more adaptive and student-centered.

The impact of RA on educational platforms cannot be fully understood without considering two key aspects: proper user training and the ethical implications associated with their use. Both elements are essential to ensure responsible implementation that respects students' rights and provide equitable access to the benefits of these technologies. In this regard, ethical and privacy concerns related to data management take on critical importance. It is imperative for educational platforms to establish clear policies regarding the collection, storage, and use of student data, ensuring the protection of personal information and respect for users' rights. Likewise, the lack of proper training for educators and students can significantly limit the effectiveness of these systems. Therefore, training in the use of these tools is crucial to maximize their potential and ensure that all stakeholders can fully benefit from the capabilities offered by recommendation systems.

Taken together, these findings indicate an intermediate stage of maturity the adoption of hybrid variants and deep models has not been accompanied by comparable pedagogical evaluation standards nor by robust metrics of diversity, equity, or explainability. Progress will require reproducible protocols, integration of longitudinal learning out-comes, and bias control mechanisms before scaling these solutions.

4. Conclusions

The integration of AI into e-learning environments demonstrates a significant practical impact by enabling continuous learning techniques through systems capable of storing large volumes of information and generating recommendations and reports useful for educators. In applied terms, these systems make it possible to identify students' strengths and weaknesses, dynamically adjust instructional strategies, and optimize the allocation of educational resources on digital platforms, resulting in potential improvements in timely feedback, personalization of learning pathways, and efficiency in progress monitoring. Among the study's novel contributions, we highlight the comparative synthesis of different RA and their performance across diverse educational contexts, as well as the development of an analytical framework that balances accuracy, relevance, ethics, and privacy, emphasizing the role of transparency and user control over their data. In relation to the existing literature, our findings converge with studies reporting increases in the relevance of recommendations and student engagement when collaborative and hybrid approaches are employed; however, they diverge from works that indicate risks of echo chambers and reductions in critical thinking under excessive personalization, underscoring the need for explicit mechanisms for content diversification and for assessing formative impact beyond precision/recall metrics. From this comparison, it follows that there is no perfect algorithm: each approach presents limitations and implementation complexities, and its performance depends on data quality, pedagogical context, and instructional objectives.

Building on the above, we propose guidelines for future research: (i) develop and validate experimental and quasi-experimental designs that assess the adaptability of RAs in resource-constrained contexts and with students who have specific educational needs; (ii) establish comprehensive metrics that combine recommendation performance as accuracy, recall, novelty, and diversity with indicators of deep learning and critical thinking; (iii) promote open datasets and protocols to support reproducibility and audits of fairness, privacy, and transparency; and (iv) advance universalizable ethical frameworks to guide the responsible implementation of RA across different educational levels and modalities.

This review and comparative study confirm the feasibility of AI-mediated personalization in educational platforms, while delineating its limits and conditions of effectiveness: there is no universal algorithm, continuous training and contextualized evaluation improve performance, and balancing personalization, ethics, and content diversity is crucial to preserve educational quality. These results address the stated objective and the type of study conducted, providing a solid basis for informed decision-making in the design and implementation of recommendation systems in digital education, without resorting to premature conclusions about developments still in progress.

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