Role of Artificial Intelligence in the personalization of distance education: a systematic review

Rol de la Inteligencia Artificial en la personalización de la educación a distancia: una revisión sistemática

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ABSTRACT

Artificial intelligence (AI) represents a significant opportunity for the personalization and adaptation of educational systems in virtual mode. Advances in AI have been applied mainly in intelligent tutoring systems, predictive models, and personalization of resources and learning strategies. This research, which consists of a systematic bibliographic review, aimed to analyze studies on the use of AI in the personalization of learning processes in distance education. The topics and educational levels of the initiatives, main results, types of data used, most recurrent modeling techniques, and perceptions on the implementation of AI in virtual education were identified. For this research, the WoS, Scopus, Dialnet, and SciELO databases were consulted, selecting 65 documents published between 2018 and 2023. It was observed that AI is integrated outside the learning process in extracurricular support initiatives designed from predictive models of academic success, as well as within the curriculum through the development of adaptive recommendation systems that recommend resources, materials, and personalized learning paths and/or provide personalized feedback on the process. Successful uses of AI in virtual education have the potential to be adapted, depending on the objective pursued, to various disciplines, including attention to special educational needs (SEN), and to groups of students at different levels of the educational system, with a greater concentration on higher education.

Keywords: adaptive learning; e-learning; personalized learning; artificial intelligence; systematic literature review.

RESUMEN

La inteligencia artificial (IA) representa una oportunidad significativa para la personalización y adaptación de sistemas educativos en modalidad virtual. Los avances en IA se han aplicado principalmente en sistemas de tutoría inteligentes, modelos predictivos y personalización de recursos y estrategias de aprendizaje. Esta investigación, que consiste en una revisión bibliográfica sistematizada, se propuso analizar estudios sobre el uso de la IA en la personalización de los procesos de aprendizaje en educación a distancia. Se identificaron temas y niveles educativos de las iniciativas, principales resultados, tipos de datos utilizados, técnicas de modelado más recurrentes y percepciones sobre la implementación de la IA en educación virtual. Para esta investigación, se consultaron las bases de datos WoS, Scopus, Dialnet y SciELO, seleccionando 65 documentos publicados entre 2018 y 2023. Se observó que la IA se integra fuera del proceso de aprendizaje en iniciativas de apoyo extracurricular diseñadas a partir de modelos predictivos de éxito académico, así como dentro del currículo a través del desarrollo de sistemas de recomendación adaptativos que recomiendan recursos, materiales y rutas personalizadas de aprendizaje y/o retroalimentan de manera personalizada el proceso. Los usos exitosos de la IA en la educación virtual tienen el potencial de ser adaptados, según el objetivo perseguido, a diversas disciplinas, incluyendo la atención a necesidades educativas especiales (NEE), y a grupos de estudiantes de distintos niveles del sistema educativo, con una mayor concentración en la educación superior.

Palabras clave: aprendizaje adaptativo; educación a distancia; enseñanza individualizada; inteligencia artificial; revisión sistemática.

How to cite: Romero Alonso, R., Araya Carvajal, K., & Reyes Acevedo, N. (2025). Role of Artificial Intelligence in the personalization of distance education: a systematic review. [Rol de la Inteligencia Artificial en la personalización de la educación a distancia: una revisión sistemática]. *RIED-Revista Iberoamericana de Educación a Distancia, 28*(1). https://doi.org/10.5944/ried.28.1.41538

INTRODUCTION

The integration of ICT in education has led to significant transformations in teaching and learning methods (Saltos-Rivas et al., 2022). The pandemic accelerated the adoption of digital tools to support educational processes (Macías Villarreal et al., 2024), driving the search for technological solutions and adapting virtual environments for distance learning (Area-Moreira, 2021).

In this context, e-learning, understood as an educational modality where teachers and students interact at different times and places using technology as the primary means of mediation (Finch & Jacobs, 2012; García Aretio, 2020), has seen substantial growth in both academic offerings and enrollment. E-learning can be likened to distance learning, characterized by the geographic separation of instructor and student (Moore & Kearsley, 2012; Traxler, 2018), a modality that, although historically carried out through various means, has now been enriched with digital technologies. Meanwhile, virtual learning is defined as learning conducted in an environment that uses digital technologies to facilitate the teaching-learning process (Picciano, 2017), and it can occur synchronously or asynchronously (Coman et al., 2020). Online education, on the other hand, refers to an educational modality that takes place entirely over the Internet, including content delivery, activities, assessments, and interactions between students and teachers (Anderson, 2008). All these modalities share the mediation of learning through digital means, allowing institutions to use each approach according to their objectives and available resources. For this study, the concept of virtual learning will encompass any of these perspectives.

More and more institutions are offering programs in these modalities, expanding access to education (OECD, 2018). This fact attracts a broad group of people seeking to balance studies, work, and personal/family life thanks to these modalities' flexibility and reduction of geographical limitations. This growth has posed a challenge for institutions offering virtual training, as they must find strategies to support the academic success of a diverse student population (Romero Alonso & Anzola Vera, 2022). Educational platforms are constant in these modalities and adapting them to students' needs is crucial (Essa et al., 2023; Sanchez-Santillan et al., 2016). The vast amount of data generated in virtual interactions has led to exploring its potential to create systems that better respond to educational challenges (Ennouamani & Mahani, 2017). In this regard, artificial intelligence (AI), defined as the study of agents that perceive their environment and take actions (Russell & Norvig, 2020), emerges as an opportunity to personalize and adapt virtual educational systems (Ennouamani & Mahani, 2017; Ilić et al., 2023).

AI originated in the 1950s and initially focused on creating programs capable of performing specific tasks and solving fundamental mathematical problems (McCarthy, 2007). With technological advances, more sophisticated approaches emerged, such as machine learning and neural networks, which allowed machines to learn from data and improve their performance over time (Russell & Norvig, 2020). In virtual learning, intelligent techniques have been fundamental in modeling, guiding, providing feedback, and personalizing the educational experience by recommending adaptive learning paths and interfaces (Tang et al., 2021). These techniques have proven effective in enhancing student engagement (Bodily et al., 2018; Kim et al., 2016; Mamcenko & Kurilovas, 2017), increasing motivation (Hobert & Meyer von Wolff, 2019; Sharma et al., 2020; Tenório et al., 2021), and improving learning in online education (Kaliwal & Deshpande, 2021; Mangaroska et al., 2019; Mangaroska et al., 2021; Murphy, 2017). According to Tang et al. (2021), AI advances have primarily been applied to four functions within e-learning: intelligent tutoring systems, adaptive and personalized resource or learning strategy systems, profiling for prediction, and assessment systems. Dogan et al. (2023) categorize these applications into three major themes: data mining or learning analytics for implementing adaptive learning; online algorithmic educational spaces, ethics, and human agency; and detection, identification, recognition, and prediction applied to educational processes. Ilić et al. (2023) identify four typical applications of AI in enhancing e-learning systems: student modeling, learning analytics, automatic assessment, and personalized (adaptive) learning.

In recent years, the concept of Personalized Adaptive Learning (PAL) has emerged. It has been identified as a new pedagogical approach that surpasses standard e-learning facilitated by intelligent learning technologies (Peng et al., 2019). According to Al-Chalabi and Ali Hussein (2020), personalized adaptive learning adjusts content and teaching methods to individual student needs based on detailed analysis to offer more effective and engaging learning. Gligorea et al. (2023) describe it as the implementation of educational systems that adapt to individual needs to improve learning outcomes, achieving personalization through adjustments in content and teaching methods based on continuous evaluation of student progress. Peng et al. (2019) categorize PAL as an effective pedagogical methodology empowered by technology to adaptively adjust teaching strategies at different learning stages, thanks to real-time monitoring of each student's changes and differences. Essa et al. (2023) add that its effectiveness is maximized by adjusting educational methods and resources with each student's preferences.

PAL systems use adaptive recommendation as the primary AI technology, employing algorithms and machine learning techniques to dynamically tailor content recommendations based on user behavior, preferences, and context. Adaptive recommendation extends beyond education, influencing sectors such as e-commerce and entertainment, where it personalizes user experiences and enhances the relevance and effectiveness of recommendations (Adomavicius & Tuzhilin, 2005).

PAL systems are built on the premise that the learning process is unique to each student (Almohammadi et al., 2017; Hmedna et al., 2020), aligning with the personalized teaching approach, which recognizes differences in learning styles, interests, and progress rates, providing educational experiences that optimize individual potential (Pane et al., 2015). This concept, though not new, was widely adopted in traditional educational systems in the early decades of the 20th century, driven by figures like Dewey (1938), Faure (1959), Kilpatrick (1918), and Montessori (1912). Ennouamani and Mahani (2017) classify PAL systems into three categories: macro-adaptive, which, after a general assessment of student characteristics, proposes a personalized path to follow; aptitude-treatment interaction systems, which intervene at specific moments of the educational process to propose alternative personalized strategies, including Intelligent Tutoring Systems (ITS); and micro-adaptive systems, which consider the real-time situation of the student to make instructional recommendations. For PAL systems, the choice of modeling strategies is crucial, as these identify and store individual student characteristics and learning patterns, which are then used in personalization processes in virtual education (Ilić et al., 2023).

Among recent studies on AI in virtual education with a focus on personalization, the work of Apoki et al. (2022) stands out, specifically analyzing the role of intelligent pedagogical agents in the personalization of virtual learning, identifying intelligent tutoring, intelligent monitoring, and intelligent collaborative learning as their primary functions. The research by Li and Wong (2021) observes how personalized learning has undergone significant evolution from 2001 to 2018, driven by the inclusion of AI and a greater understanding of individual needs, manifested in the diversification of tools and methods used to tailor virtual education to individual student characteristics. Meanwhile, Essa et al. (2023) reviewed 48 publications on learning styles and the use of AI in adaptive educational systems, identifying the Felder and Silverman Learning Style Model (FSLSM) as the most widely used to classify students and generate recommendations. This approach has successfully adapted content and methods according to preferred learning styles, effectively supporting the learning process. The works of Almohammadi et al. (2017), Jando et al. (2017), Kardan et al. (2015), Özyurt and Özyurt (2015), Talaghzi et al. (2020), Xie et al. (2019), and Zine et al. (2019) reflect the growing interest in this perspective.

Thus, virtual education is being transformed by implementing AI, enabling more personalized learning processes. At the same time, it raises concerns about its scope (Ayala-Pazmiño & Alvarado-Lucas, 2023; Chan & Hu, 2023; Seo et al., 2021) as well as expectations about its possibilities (Chocarro et al., 2021; Emara et al., 2023; Haniya et al., 2020). In this context, it is essential to investigate AI's role in personalizing distance education and assess its effectiveness in improving teaching-learning processes, considering its contributions and challenges. This literature review enriches the academic discussion on personalized teaching by synthesizing evidence on implementing AI in personalization processes and identifying the most effective strategies and models in virtual learning environments. From this perspective, research was identified that analyzes the use of artificial intelligence to personalize learning processes in virtual education. The search was based on the following questions:

- What types of initiatives have been implemented to personalize the learning experience in e-learning training based on artificial intelligence techniques?
- What results have the personalization initiatives implemented in virtual training achieved?
- What types of data are used by systems to personalize learning recommendations?
- What modeling techniques are used to develop intelligent systems with precise applications to personalize virtual learning?
- What perceptions exist in educational communities regarding implementing this technology for virtual learning?

METHODOLOGY

This research is a systematic literature review, a widely used methodology for analyzing and exploring a specific area of knowledge, which allows for identifying main trends and currents, gaps, and research opportunities (Codina, 2018). It was deemed appropriate for evaluating and synthesizing academic output using Artificial Intelligence to personalize virtual learning.

The study followed the four phases defined by the SALSA framework, an acronym for Search, Appraisal, Synthesis, and Analysis (Grant & Booth, 2009). The first phase, search, according to Codina (2020), requires declaring the sources and search procedures used to ensure the rigor and replicability of the review, explicitly stating the search equations employed in specific databases. In this case, the databases WoS, Scopus, Dialnet, and SciELO were consulted, and search formulas with Boolean connectors were configured using key concepts: ("artificial intelligence" OR AI), ("virtual learning" OR "virtual teaching" OR "distance education" OR e-learning), (Adaptability OR "personalized learning" OR "adaptable learning" OR "adaptive learning"), resulting in the identification of a total of 530 publications.

During the appraisal phase, the documents found were reviewed to ensure they all met the following inclusion criteria:

- Focused on the use of AI for learning personalization.
- Virtual education experiences utilizing LMS platforms.
- Published within the last five years.

Additionally, to address all the research questions posed, two more criteria were added, for which it was only necessary that the included studies meet one of them:

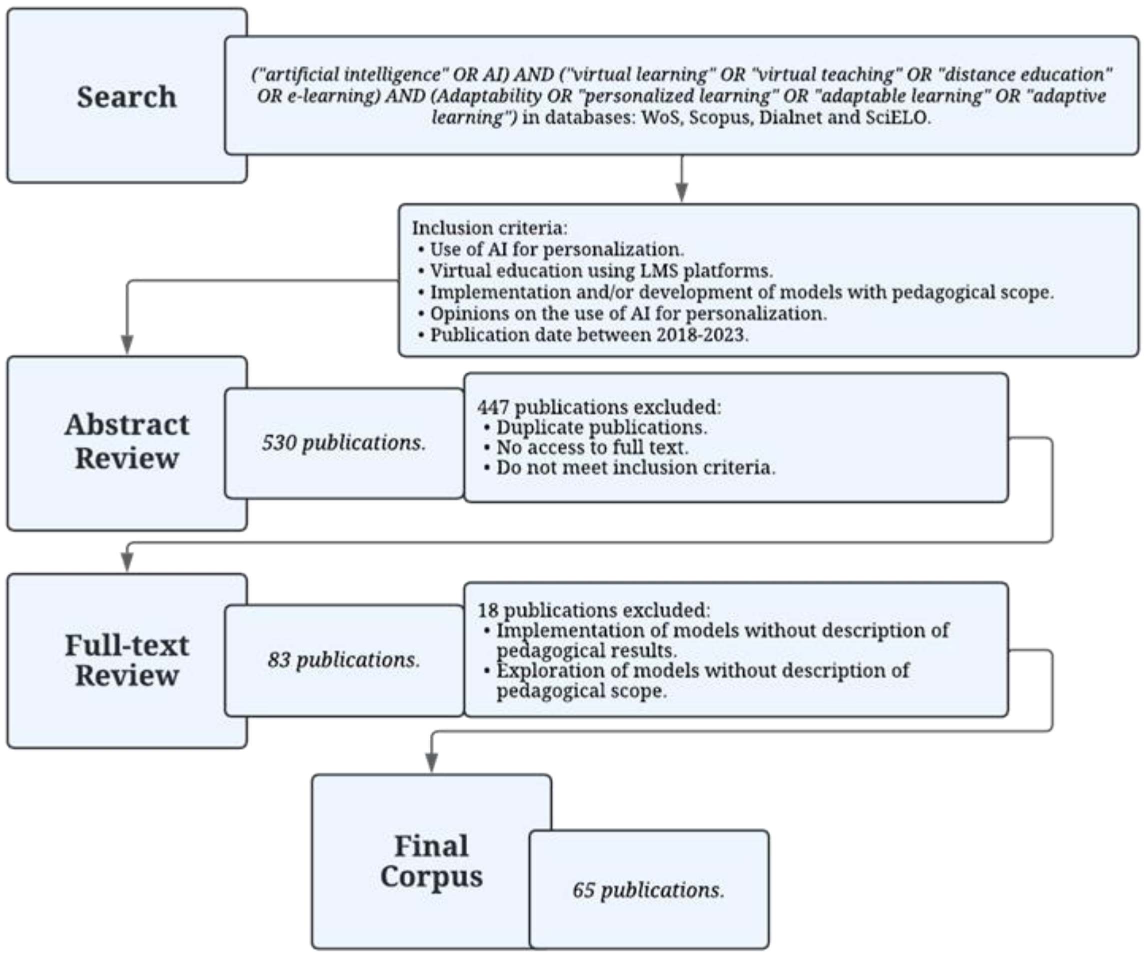
- Implement and/or develop mathematical data processing models with pedagogical scope for learning personalization.
- Opinions of educational agents on the use of AI for learning personalization.

The following exclusion criteria were also applied to avoid selecting certain studies:

- Studies discuss AI in virtual education but do not apply it to learning personalization processes.
- Descriptions only of the data modeling process without detailing the contribution to learning personalization.
- Use of AI in face-to-face learning.

Applying these inclusion and exclusion criteria to the abstracts provided by the analyzed databases, duplicate and inaccessible documents were discarded, resulting in 87 documents for full reading. Subsequently, studies that only described the construction of mathematical models or that used AI in face-to-face education systems were excluded, selecting 65 publications as the final corpus. Figure 1 details the workflow carried out during these two phases.

Figure 1
Workflow of search and appraisal phases



Note: Prepared by the authors.

Finally, the analysis and synthesis phases of the selected documents were developed, for which an analysis matrix was generated, summarizing relevant information about each document, including aspects such as the application context, methods used, and results obtained. Based on these summaries, a content analysis was conducted to identify the main topics addressed by the studies, classify them, and structure the thematic development. This process began with open coding (Saldaña, 2013; Staller, 2015), in which codes were identified and assigned to the content of the summaries, which were then grouped according to similarity criteria into broader categories reflecting the central themes of the research corpus. This approach facilitated the organization of the results and allowed for identifying relationships between the analyzed studies, enriching the synthesis and interpretation of the findings.

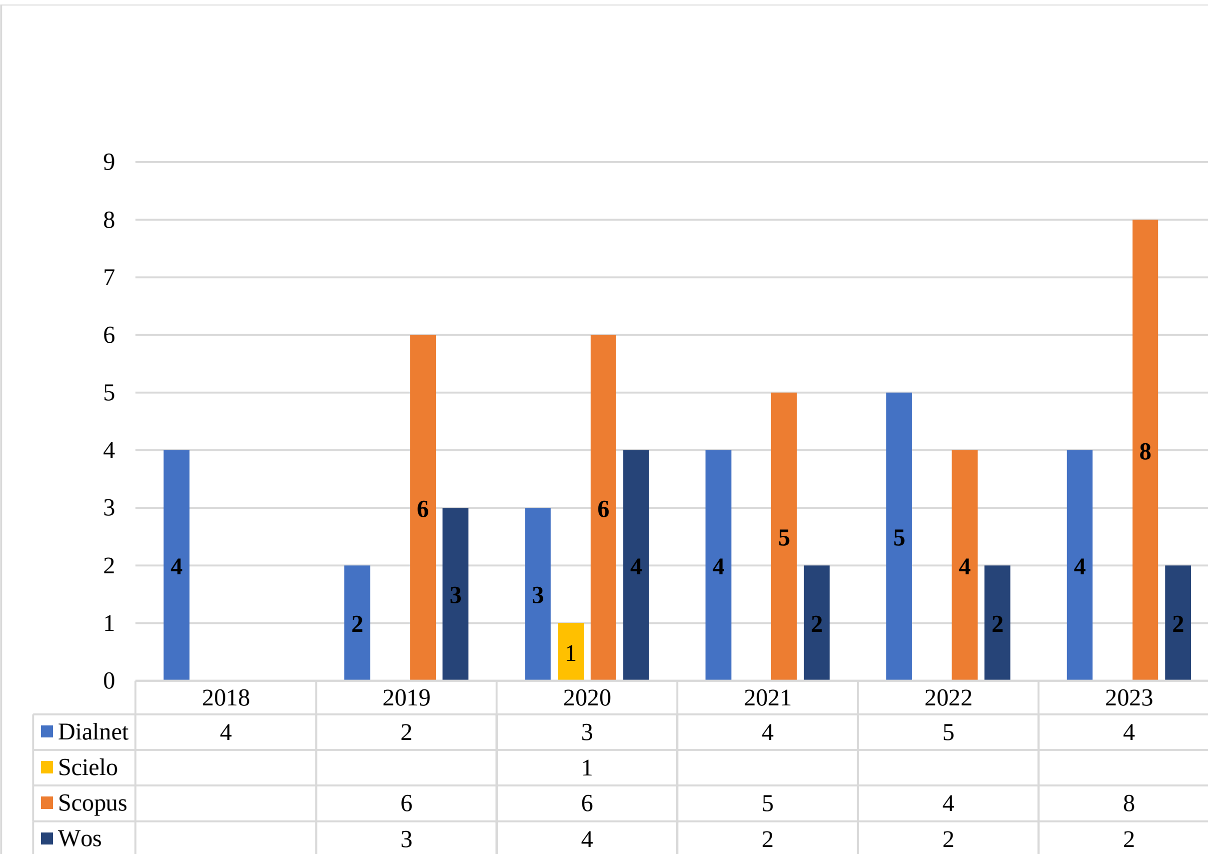
RESULTS

Overview

The document corpus includes publications from 2018 to October 2023 from the four indicated databases. As shown in Figure 2, academic output on the topic has increased since 2019, remaining relatively constant throughout the analyzed period and reaching the highest number of publications in 2020 (14) and 2023 (14). Scopus (29) and Dialnet (22) were the databases that provided the most analyzed documents.

Figure 2

Number of Documents by Year of Publication and Database

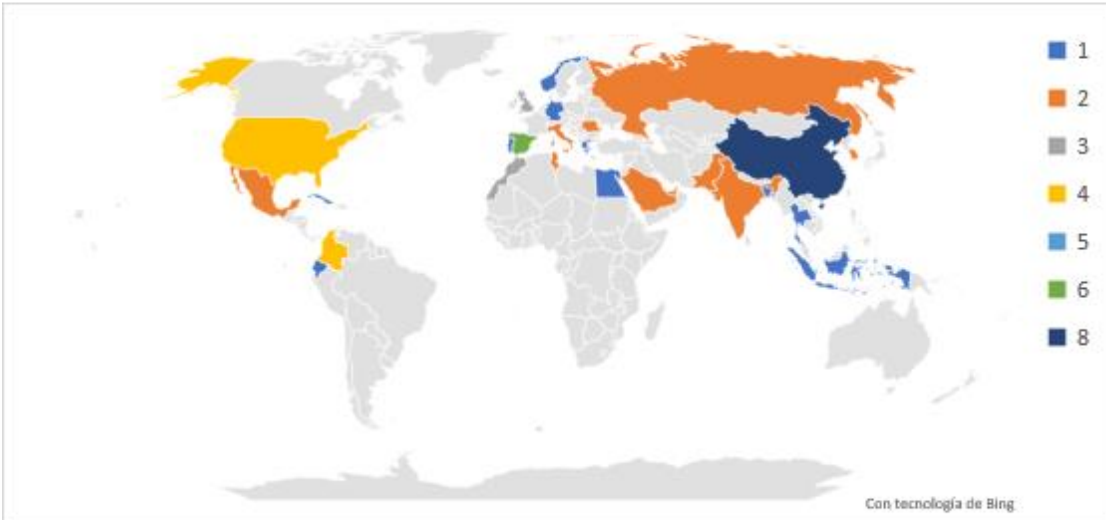


Note: Prepared by the authors.

Regarding the geographic distribution of the studies, Asia is the continent with the highest production (43%), with countries such as China (8) and Taiwan (6) standing out, also diversifying initiatives across different educational levels. Spain's production is significant (8), and when combined with other European countries, it accounts for 29% of the academic output on this topic. Figure 3 shows the academic output distribution by country.

Figure 3

Distribution of Documents by Geographic Region



Note: Prepared by the authors.

Thematic Analysis

This section presents the development of the previously identified themes, describing the content of the analyzed articles and emphasizing their findings and contributions to the research questions.

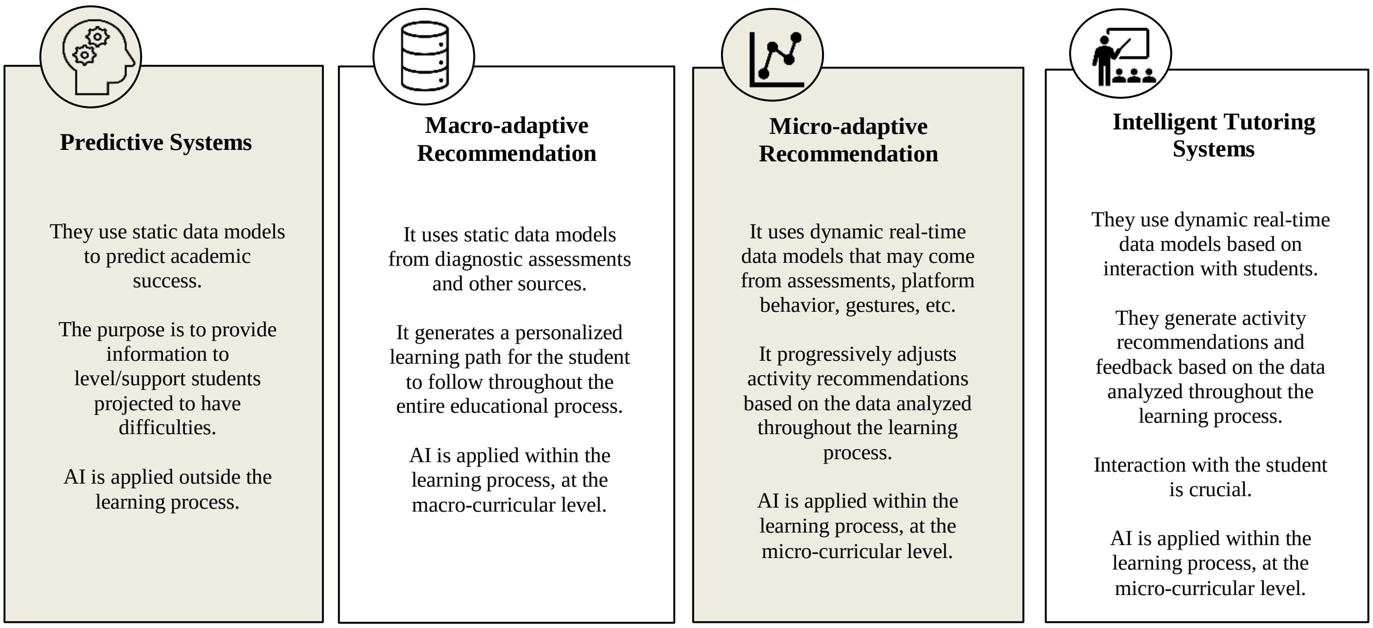
It is worth noting that the primary uses of AI in the personalization of virtual learning are centered on the creation of monitoring systems and predictive models of academic progression (from which student support initiatives are derived) and the development of adaptive systems that recommend learning paths/resources/materials and/or provide feedback on the process (Al-Chalabi & Ali Hussein, 2020; Apoki et al., 2022; Ilić et al., 2023; Zawacki-Richter et al., 2019).

It is essential to mention that the chosen categories are not necessarily exclusive, as the categories of "Mobile Learning" and "Support Systems for Students with Special Needs" could be understood as subcategories of "Macro and Micro Adaptive Recommendation Systems." However, they have been analyzed independently to highlight more specific cases of adaptive system implementation, emphasizing their relevance and particularity.

All these applications selected in our study rely on AI to generate processes inside and outside the classroom that support students based on their differences or specific performance to enhance their academic success. Each system uses relevant data analysis models to generate successful predictions. AI can act at both the macro and microcurricular levels in virtual education and function with or without interaction with the student (see Figure 4). Additionally, students can be given varying autonomy to follow AI recommendations, as with Intelligent Tutoring Systems (ITS) (Ennouamani & Mahani, 2017).

Figure 4

Curricular Application of AI-based Systems in Distance Education



Note: Synthesized by the authors.

Monitoring/Support Systems for Academic Success

Predictive analytics in higher education has become a fundamental tool for promoting academic success. These models rely on historical and highly predictive data to identify critical factors in student performance. For example, Kar et al. (2023) demonstrated that the duration of class connections, the type of institution, and the financial situation are critical determinants for students' adaptability to online education. Embarak (2022) used the Internet of Behavior to offer personalized guidance, while López-Zambrano (2021) highlighted the importance of using activities and resources in Moodle to improve prediction accuracy.

Predictive models are also used to assess academic performance, as evidenced in Silva et al. (2022), which compares current grades with historical data to manage support tutoring. Tsai et al. (2020) incorporated variables such as performance, absences, and loan requests to refine predictions. Additionally, Lee et al. (2021) demonstrated how these models apply to lower educational levels by predicting English learning outcomes.

Prediction accuracy increases with the incorporation of additional data, as indicated by Rincon-Flores et al. (2022). Finally, multimodal data, including eye-tracking and facial expressions, has proven effective in predicting engagement and performance, as observed by Sharma et al. (2019). These advances highlight the potential of predictive models to optimize academic support.

Exploration of Models and Prototypes

This category includes several studies focused on proof-of-concept and experimental designs for creating models that personalize virtual education, offering critical insights for developing predictive and adaptive systems applicable across various fields and educational levels. Ahmadaliev et al. (2019) and Shvetsov et al. (2020) developed models for adaptive recommendation systems targeting high school mathematics and higher education computer science students. Bennani et al. (2022) proposed a classification model for a gamified mobile learning environment for primary school students. Muse et al. (2023) presented an initial linguistic model for automatically generating educational questions. Similarly, Bogarín Vega (2018) created a predictive model for dropout rates in a psychology course, considering both passed and failed students.

In the quest for more accurate recommendation systems, Ogunkunle and Qu (2020) developed an index that improves recommendation matching by adding students' attributes and prior achievements using decision trees and iterative dichotomizers. Soui (2021) employed the NSGA-II multi-objective evolutionary algorithm to recommend educational resources. Yao and Wu (2022) explored Bayesian algorithms to identify learning blind spots. Azzi et al. (2020) used neural networks to analyze the time and frequency of visits to learning objects, adjusting recommendations according to difficulty and student level. Yang et al. (2023) employed multimodal networks and k-means to recommend musical scores suitable for different knowledge levels in music education. Alghamdi et al. (2020) developed prototypes for adaptive assessment systems, and Sapsai et al. (2023) designed a visualizer panel that guides educators by analyzing student attributes, learning styles, and success potential. Additional studies, such as those by Rooein (2019), Vasilateanu and Turcus (2019), and Xiaogang (2019), focused on optimizing the allocation of personalized resources using artificial intelligence.

As shown in Figure 5, various AI modeling algorithms or techniques are diversified across a broad spectrum depending on the required application. Natural language processing, classification, and clustering are the most widely used techniques.

Figure 5
AI Modeling Algorithms for Virtual Learning Personalization

	Predictive models of academic success	Macro-adaptive systems	Micro-adaptive systems	STI/micro-adaptive systems
Unspecified statistical technique	1	1	1	0
Natural Language Processing (NLP)	0	0	8	4
Neural Networks (various)	2	0	5	3
Multilayer Perceptron Algorithm	2	1	3	2
Random Forest	3	1	2	0
Bayesian Networks	1	1	1	2
Ensemble technique	3	1	0	0
Classification/Clustering technique	4	2	8	3
Backpropagation Algorithm	0	0	3	0
Optimization technique	1	3	1	1
Genetic Algorithm	1	3	0	0
K-nearest neighbors (KNN)	3	1	1	0
K-means	0	1	1	2
Decision Tree	2	0	3	0
Regression (various)	1	1	1	0
Support Vector Machines (SVM)	2	0	4	0
Rule-Based Techniques/Reasoning	0	1	4	4
Ontology-Based technique	1	0	1	0
Recommendation Based on Collaborative Filtering	0	1	2	0
Fuzzy Logic	1	0	3	0
Gradient Analysis Techniques (various)	1	1	5	0
Others	6	6	15	6

Note: Prepared by the authors.

Intelligent Tutoring Systems (ITS)

The application of artificial intelligence in education has enabled the development of Intelligent Tutoring Systems (ITS), which offer real-time recommendations and feedback to students, adapting to their characteristics and needs. Research has shown that these systems can significantly improve learning in virtual environments (Apoki et al., 2022; Davies et al., 2021; Kaiss et al., 2023). In higher education, ITS facilitates the mediation of learning. Martín Coronel (2022) developed a model that uses rule-based reasoning to provide personalized recommendations in computer science, considering students' competencies and preferences. Haq et al. (2020) also developed an ITS in the same field, focusing on collaborative learning and supporting interaction between students and tutors. To achieve greater precision in recommendations, Veeramanickam et al. (2023) implemented a model based on the Internet of Things that analyzes various parameters, such as keyword searches and students' eye movements, to personalize study materials.

Ventura (2022) presented an ITS for music education that uses an adaptive algorithm to correct errors in harmonization exercises.

Interaction is crucial in ITS. Davies et al. (2021) and Kaiss et al. (2023) developed chatbots trained with information on students' professional experience and learning styles, designed to answer questions and recommend tasks during the educational process. In the field of algebra, Montoya Pérez and Mateus Santiago (2018) developed an ITS that uses neural networks and gamification to recommend activities, while López Jiménez (2023) implemented a gamified system that offers personalized feedback based on cognitive diagnostics. Lu et al. (2021) demonstrated that their ITS, through deep neural networks, can analyze students' status and weaknesses to facilitate tutor intervention.

ITS has also been incorporated into school education, particularly in mathematics. Troussas et al. (2019) developed an ITS for primary education that uses clustering to group students according to their knowledge level, facilitating personalized tutoring and encouraging collaboration. In secondary education, Thomas et al. (2023) created an ITS that supports tutor training in mathematics, simulating real-world scenarios to improve content teaching and student motivation. These advancements highlight the potential of ITS to transform education by personalizing its content and improving learning outcomes at various educational levels.

Learning Experiences with Macro and Micro Adaptive Recommendation Systems

The literature on using artificial intelligence (AI) to personalize virtual learning primarily focuses on testing adaptive recommendation systems that cater to individual student needs. Ennouamani and Mahani (2017) proposed a classification based on the didactic-curricular design stage, where AI is used for recommendation (see Figure 4).

From the perspective of macro-adaptive recommendation, the studies by Azcorra Novelo and Gallardo Córdova (2022), Ingkavara et al. (2022), and Daghestani et al. (2020) focus on personalized learning paths using statistical techniques such as multiple regression and clustering. Azcorra Novelo and Gallardo Córdova base their recommendations on learning diagnostics, while Ingkavara et al. also consider student attitudes and self-assessment. Daghestani et al., for their part, classify students according to their player type in a gamified environment. Ma et al. (2023) employ swarm algorithms to analyze cognitive levels and learning styles, while Vanitha et al. (2019) hybridize collaborative and genetic optimization algorithms, integrating emotions and cognitive abilities. Lhafra and Abdoun (2023) use genetic evolutionary algorithms to adapt learning situations to student profiles. Krechetov and Romanenko (2020) apply a model based on the speed of forgetting in higher education to recommend learning paths. Pardamean et al. (2022) implement a system in primary education that uses learning styles to recommend appropriate materials through collaborative filtering.

Meanwhile, micro-adaptive recommendation systems, such as those developed by Choi and McClenen (2020), González Boticario and Díaz Rozo (2018), Kushnarev et al. (2020), and Wang et al. (2019), adjust the number of recommended exercises according to previous performance and student progress, helping to level learning in real-time. Al-Chalabi et al. (2021) and Lihua (2021) implement adaptive systems that offer personalized content at the beginning and middle of the course, adjusting recommendations based on assessment performance. Gan et al. (2021) developed a mixed model that, in addition to an initial diagnosis, uses browsing history data to update recommendations continuously. Wu et al. (2023) designed a real-time engagement detection system that adapts recommendations based on student interactions, improving their engagement and self-efficacy. Álvarez et al. (2018) integrated collaboration strategies and their evaluation into an adaptive system, and in a later application (Álvarez et al., 2020), developed a model in a gamified environment whose serious game, based on intelligent agents and collaborative learning, motivates active participation in learning activities.

As shown in Figure 6, various macro and micro-adaptive systems and predictive models use different data types to build their models and generate predictions or recommendations—the most commonly used data are previous activity results, knowledge level, and platform interactions. The quality of these data and their relevance to the personalization goals are critical to the success of both curricular and support activity recommendations.

Figure 6

Types of Data Used in AI Models for Virtual Learning Personalization

	Predictive models of academic success	Macro-adaptive systems	Micro-adaptive systems	STI/micro-adaptive systems
Knowledge level	1	1	6	4
Learning style	1	3	4	2
Platform interaction (time, entries)	2	2	6	2
Interests/preferences	0	1	3	1
Results in previous activities	4	1	7	3
Prior Knowledge	0	2	3	2
Student characterization	2	1	2	1
Cognitive level	0	1	4	1
Emotional state	0	1	1	0
Facial/gestural/ocular tracking	1	1	1	1
Attitude/engagement	1	0	1	1
Psychological profile	0	0	0	2
Others	1	1	6	2

Note: Prepared by the authors.

In summary, macro and micro adaptive recommendation systems show high potential for personalizing learning and improving educational outcomes. They leverage AI to tailor paths and content to individual student characteristics and behaviors.

Mobile Learning

Studies on adaptive learning in mobile environments show high efficacy due to the ubiquity and autonomy these environments bring to the educational process (Bernacki et al., 2020; Kanaki et al., 2022). These experiences are based on micro-adaptation, offering personalized activity recommendations based on data collected during all phases of learning. For example, Palomares Marín (2021) analyzed Duolingo, highlighting that the combination of interface design, multimedia, usability, gamification, and AI applied to the app's architecture significantly improves language learning. Personalization and instant feedback make the experience comparable to a human tutor's. Liu et al. (2019) investigated an algorithm recommending educational resources based on learning history and user preferences. Adnan et al. (2019) describe an application that uses contextual information to support decision-making in programming, demonstrating its success in improving learning through accurate and tailored recommendations.

Support Systems for Students with Special Needs

Four adaptive learning experiences focused on addressing students' unique needs were selected, demonstrating the utility of recommendation systems. From the perspective of macro-adaptations, Alsobhi and Alyoubi (2019) developed a system that correlates each type of dyslexia with specific learning styles, allowing material to be adapted to individual student needs. Wang and Yang (2020) used neural networks to support deaf and hard-of-hearing students, overcoming the limitation of teachers not knowing sign language. Their platform offers personalized learning paths based on students' prior knowledge.

Ojeda Castelo (2022) created a system based on motion sensors for students with various special needs. This system collects information on students' reactions to proposed activities and adjusts the learning sequence according to these interactions, showing promising results in participation and acceptance of the learning environment. Finally, Standen et al. (2020) developed a platform that integrates emotional state recognition to personalize learning activities for students with intellectual disabilities. Personalization according to students' needs and emotional states increased their engagement and created a more supportive learning environment.

Perceptions of AI Opportunities for Learning

Several studies analyzed students', parents', and teachers' perceptions of artificial intelligence (AI) in education and the opportunities it offers. Overall, opinions are positive, recognizing that AI can improve communication in virtual environments and personalize learning according to individual needs. However, concerns about privacy, information security, and the potential dehumanization of interactions also arise.

Ayala-Pazmiño and Alvarado-Lucas (2023). Chan and Hu (2023) and Seo et al. (2021) investigate the general adoption of AI tools, finding that students value their potential to enhance virtual teaching. Highlighted benefits include improved communication, personalized interactions, timely feedback, and strengthening skills where weaknesses exist. However, ethical concerns such as the risk of excessive surveillance and data privacy protection are also noted. Ayala-Pazmiño and Alvarado-Lucas (2023) emphasize the importance of adequate infrastructure and teacher training to implement AI effectively.

Other studies focus on the perception and satisfaction of specific AI tools, such as chatbots, intelligent tutors, and recommendation systems. Chocarro et al. (2021) analyze teachers' acceptance of a chatbot, highlighting that ease of use and perceived usefulness are crucial factors. Teachers value the support these systems provide, allowing them to manage class time better and offer personalized help to students. Emara et al. (2023) investigate parents' satisfaction with an intelligent tutor in a high school who recognizes its pedagogical advantages, such as stimulating independent learning and improving motivation. For their part, Haniya et al. (2020) evaluate a learning analytics system driven by Machine Learning and Big Data, finding a high level of student agreement on its usefulness for monitoring academic progress and optimizing learning according to their needs and time availability.

In summary, AI in education is seen as a valuable tool for personalizing and enhancing teaching, although its implementation presents challenges and concerns that must be addressed.

DISCUSSION

The analysis identifies the main applications of artificial intelligence (AI) in virtual education, highlighting its ability to personalize learning. These applications focus on four key areas: support systems based on predictive models of academic success, learning adaptation through macro and micro-adaptive recommendation systems and the use of Intelligent Tutoring Systems (ITS). These systems not only optimize learning but also address students' individual needs.

This study expands on the uses observed in other works (Al-Chalabi & Ali Hussein, 2020; Apoki et al., 2022; Essa et al., 2023; Ilić et al., 2023; Li & Wong, 2021) by including predictive models that propose support strategies, even if they do not exclusively refer to the learning process. These models contribute to addressing individual needs identified through the application of AI.

AI applications in virtual education are versatile and can be adapted to any field of knowledge. However, their use is more common in STEM disciplines and higher education, where most experiences are concentrated. Initiatives for students with special educational needs have also been identified, demonstrating the inclusive potential of these technologies (Standen et al., 2020; Wang & Yang, 2020). The results of implementing these technologies show improvements in learning, motivation, and student participation (Haq et al., 2020; Kushnarev et al., 2020; López Jiménez, 2023; Wang et al., 2019). Additionally, there is widespread acceptance of these technologies by educational stakeholders (Chocarro et al., 2021; Haniya et al., 2020), although concerns exist regarding the use of data to personalize learning (Ayala-Pazmiño & Alvarado-Lucas, 2023; Chan & Hu, 2023; Seo et al., 2021).

It is essential to closely monitor the data types used by adaptive recommendation systems to personalize learning. Macro-adaptive systems tend to generate recommendations based on an initial assessment of knowledge and static criteria such as learning styles (Pardamean et al., 2022) or tested behaviors, e.g., player type in a gamified environment (Daghestani et al., 2020). In contrast, micro-adaptive systems work with data generated during the learning process, such as platform interactions (Bennani et al., 2022; Wu et al., 2023), connection time (Azzi et al., 2020; Ma et al., 2023), reactions to activities (Ojeda Castelo, 2022; Sharma et al., 2019), and progress in partial assessments (Al-Chalabi et al., 2021; Kushnarev et al., 2020). Understanding the evolution of these models and the combination of data used is a relevant area of study to observe.

The studies analyzed hardly address the adaptation of virtual teaching or the challenges teachers face when adopting adaptive recommendation technologies, a crucial aspect given the redefinition of the teaching role implied by this change. Like Li and Wong (2021), it is observed that while the technologies allow for greater personalization, teachers must be trained to integrate these tools into their pedagogical practices effectively.

The analysis also highlights the use of various techniques for data modeling, depending on the system's implementation objective. Techniques used to optimize predictive and classification models include Decision Trees (Ogunkunle & Qu, 2020), multi-objective evolutionary algorithms (Soui, 2021), Bayesian networks (Bogarín Vega, 2018; Yao & Wu, 2022), neural networks (Azzi et al., 2020; Muse et al., 2023; Xiaogang, 2019), natural language processing (Vasilateanu & Turcus, 2019), educational data mining (Ahmadaliev et al., 2019; Bogarín Vega, 2018; Ogunkunle & Qu, 2020), multimodal networks (Yang et al., 2023), fuzzy logic (Alghamdi et al., 2020), and modeling algorithms (Bennani et al., 2022; Rooein, 2019; Sapsai et al., 2023; Shvetsov et al., 2020). These techniques are standard in micro-adaptation and intelligent tutoring systems, the central trend in the analyzed publications.

CONCLUSIONS

As noted by Apoki et al. (2022), Gligorea et al. (2023), and Li and Wong (2021), the integration of AI in virtual education represents a significant opportunity for learning personalization, allowing the educational process to be tailored to students' individual needs. This approach positively impacts academic performance, motivation, and student participation, as confirmed by the literature analyzed. Unlike the study by Li and Wong (2021), we observe that various studies regarding the types of data and AI algorithms used provide a solid foundation for implementing these systems.

This study introduces new insights in two key areas: it analyzes publications not only in terms of resource or learning path recommendations (Al-Chalabi & Ali Hussein, 2020; Apoki et al., 2022; Essa et al., 2022; Gligorea et al., 2023; Li & Wong, 2021), but also in the inclusion of experiences that allow for student support outside the classroom. Additionally, it addresses the technical and pedagogical aspects of these experiences, synthesizing essential information for AI implementation, whether in predictive models or adaptive recommendation systems. It examines the characteristics of the data and algorithms used, always keeping their pedagogical significance in perspective.

This review provides a broad and updated overview of AI applications for personalizing distance education and identifying effective practices, strategies, and models for improving virtual teaching. It also suggests future research directions, such as further studying the types of data and parameters used and their efficiency in adaptive prediction or recommendation, to develop more robust models aligned with recognized educational approaches and ensure the effectiveness of these interventions; exploring changes in the teaching role with the integration of these technologies; and investigating the perceptions of different stakeholders involved in distance learning, considering the ethical and information security aspects to ensure integrity and improve acceptance and pedagogical effectiveness.

The main limitation of this research lies in the selection of keywords and databases, which, while delimiting the study's scope, may restrict its reach and exclude other relevant experiences.

As emphasized by Gligorea et al. (2023), although the benefits of using AI to personalize virtual learning are evident, concerns about the use of personal data remain a significant challenge that must be addressed. Students' perceptions indicate concerns about privacy and information management, underscoring the need for a solid ethical framework to accompany the implementation of these technologies.

In conclusion, AI in virtual education can improve educational outcomes and make learning more inclusive and adaptive. However, it is essential to continue researching and developing solutions that optimize learning while respecting and protecting students, limiting the use of this data for educational purposes.

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Date of reception: 1 June 2024
Date of acceptance: 19 August 2024
Date of approval for layout: 25 September 2024
Date of publication in OnlineFirst: 15 October 2024
Date of publication: 1 January 2025