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Review Article

Mapping the intelligent classroom: Examining the emergence of personalized learning solutions in the digital age

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ABSTRACT

It may seem that learning platforms and systems are a tired topic for the academic community; however, with the recent advancements in artificial intelligence, they have become relevant to both current and future educational discourse. This systematic literature review explored platforms and software supporting personalized learning processes in the digital age. The review methodology followed PRISMA guidelines, searching Scopus and Web of Science databases. Results identified three main categories: artificial intelligence, platforms/software, and learning systems. Key findings indicate artificial intelligence plays a pivotal role in adaptive, personalized environments by offering individualized content, assessments, and recommendations. Online platforms integrate into blended environments to facilitate personalized learning, retention, and engagement. Learning systems promote student-centered models, highlight hybrid environments' potential, and apply game elements for motivation. Practical implications include leveraging hybrid models, emphasizing human connections, analyzing student data, and teacher training. Future research directions involve comparative studies, motivational principles, predictive analytics, adaptive technologies, teacher professional development, cost-benefit analyses, ethical frameworks, and diverse learner impacts. Overall, the dynamic interplay between artificial intelligence, learning platforms, and learning systems offers a mosaic of opportunities for the evolution of personalized learning, emphasizing the importance of continuous exploration and refinement in this ever-evolving educational landscape.

Keywords: improving classroom teaching, data science applications in education, human-computer interface, learning communities, distributed learning environments

INTRODUCTION

Education is currently immersed in an era of profound and rapid transformations, largely driven by the rapid development of advanced digital technologies, with a particular emphasis on artificial intelligence (AI) and machine learning (Jun et al., 2024; Liu et al., 2018; Vhatkar et al., 2023). This context has given rise to the concept of "Education 4.0," which is conceived as the deployment of educational practices mediated or supported by technologies of the fourth industrial revolution (Marzal & Vivarelli, 2024). Thus, the educational domain is navigating an era where the synergy between traditional pedagogy and advanced technologies is redefining learning methodologies, ushering in times of innovation and adaptability that seek to prepare students for the challenges of an increasingly dynamic and technology-driven world.

In this evolving educational paradigm, many researchers argue for a redefinition of the student role, advocating for more active, flexible, autonomous, and personalized approaches to address the challenges of 21st century education (Ibrohim et al., 2023; Muar, 2019; Nayan et al., 2024). However, it's important to note that the effectiveness of these approaches may vary across different contexts and learner groups. In response to this landscape, educational innovation must generate creative proposals that adapt, empower, and enhance student learning in a context of constant and unpredictable technological change (Kuleto et al., 2021). As the educational landscape evolves, students must transition from passive recipients to active participants, engaging dynamically with content and methodologies tailored to their individual needs, thus fostering a generation of learners equipped to navigate and thrive in the complex and ever-evolving global landscape.

According to Babu and Wooden (2023), personalized learning models play a fundamental role in this transformation. These models leverage various existing methodologies aimed primarily at skill development through interactions between humans and technology, whether in the form of software or machines (Hernandez-Cardenas et al., 2022). In this regard, specialized platforms and software are playing a crucial role in facilitating these interactions, enabling levels of personalization that were previously difficult to imagine (Alamri et al., 2021). So, the dynamic fusion of pedagogy and technology underscores the evolving landscape of education, where personalized learning becomes a cornerstone, fostering tailored educational experiences and equipping learners for the demands of the modern knowledge ecosystem.

Taking the above into consideration, Chen et al. (2020) point out that AI in particular is taking personalized learning to an unprecedented level. It has equipped educational platforms with enhanced capabilities through the application of machine learning, natural language processing, and learning analytics (Rienties et al., 2020). These capabilities enable platforms to adapt content and learning experiences more dynamically, aiming to align with individual student needs and preferences (Alamri et al., 2021). While this personalization shows promise, it's crucial to acknowledge that the precision and effectiveness of such adaptations are still subjects of ongoing research and debate in the educational community. Thereby, the infusion of AI in personalized learning not only augments adaptability but also signifies a transformative leap toward precision, responsiveness, and individualization in the educational landscape.

The development of this topic has sparked significant academic discussions and research tensions. While some researchers see great potential in AI-driven personalized learning, others express concerns about its implementation and impact. Addressing these diverse perspectives is crucial to establishing a balanced framework for discussion and to guide the thoughtful integration of AI in educational practices (Kumar Tyagi et al., 2023). In this regard, it is essential to highlight that the use of AI in education also raises significant questions and debates. On one hand, there are advocates like (Ali, 2023), who emphasize its potential to democratize education by offering personalized and accessible learning to a wide range of students. On the other hand, authors like Sharma and Kumar (2023) express legitimate concerns about potential negative effects, such as the risk of widening educational disparities or the loss of human connection in the learning process. Accordingly, The discourse surrounding the integration of AI in education is, therefore, multifaceted, necessitating a nuanced and comprehensive examination of its implications and potential consequences.

From a research perspective, we are faced with an ambiguous landscape, where much has been published on personalized education but very little about its relationship with supporting platforms or software, as depicted in **Figure 1**.

In this regard, an initial look at the published literature on personalized learning and the use of digital technologies such as AI reveals some topics of particular interest to educational researchers. These include the pedagogical foundations and approaches (Kaur, 2021), the technical capabilities required to enable the incorporation of AI in education (Bura et al., 2023; Hui, 2023; Pokrivcakova, 2019), the various formal and informal contexts of AI's educational applications (Nguyen et al., 2023), evidence of effectiveness and impacts of AI's educational use on students, ethical considerations and potential biases (Swagatika et al., 2023), barriers and facilitators of educational AI implementation, and finally, the main platforms and software for personalized learning (Gong, 2022), which is the specific focus of interest in this article.

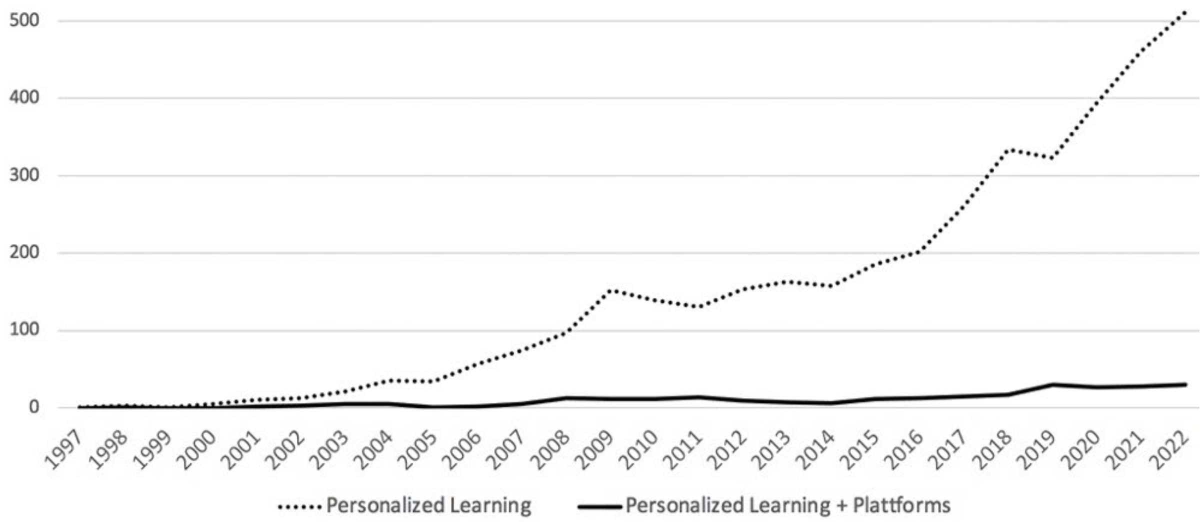

Figure 1. Research on personalized learning and platforms (Source: Authors' own elaboration using data retrieved from Scopus)

In this context, from the perspective of educational innovation, it becomes imperative to generate proposals that adapt, enhance, and improve student learning, leading to a constant and intentional transformation of the vision and educational actions to enhance the components, actors, structure, and management of current education (Ramírez Montoya et al., 2022).

Considering the above, both Alamri et al. (2021) and Ghiasabadi Farahani et al. (2022) mention that platforms can be incorporated into blended learning environments to facilitate student learning, retention, and engagement, even as it is acknowledged that these interests change rapidly over time.

In line with the above, this review aspires to provide a comprehensive and evidence-based insight into the current state and future of platforms and software for personalized learning. Thus, the findings of this review are intended to inform both research and practices in this field of educational innovation, contributing to maximizing the potential of these technologies to empower 21st century learning while respecting ethical principles and promoting equity in education.

Considering the relevance and complexity of this topic, we propose conducting a systematic literature review to explore in-depth the platforms and software used to support personalized learning processes in the digital age. Through this article, we aim to synthesize the current state of knowledge on how technological innovations are impacting educational personalization in both formal and informal educational settings.

Rationale

While there has been extensive research on personalized learning in general, there is a lack of comprehensive synthesis specifically focused on the platforms and software enabling personalized learning in the digital age. Previous reviews have examined platforms and software broadly within the context of e-learning, m-learning, and other educational modalities that make intensive use of digital technologies. However, the recent advancements in artificial intelligence are revealing a field of transformative possibilities that go beyond mere improvement of existing systems or educational processes. This transformative potential of AI in personalized learning platforms and systems has not been adequately covered by previous reviews.

Also, this review addresses that gap by providing an up-to-date, rigorous assessment of the current landscape of personalized learning platforms and software, with a particular focus on AI-driven innovations. By synthesizing findings across artificial intelligence, learning management systems (LMS), adaptive technologies, and other digital tools, this review offers practical insights to guide educators and policymakers in selecting and implementing effective personalized learning technologies. Additionally, by identifying trends, challenges, and areas for future research, this review aims to advance the field's understanding of how to leverage emerging AI technologies to create not just improved but fundamentally transformed personalized learning environments.

Ultimately, this systematic examination of personalized learning platforms and software, with a spotlight on AI's transformative role, will help bridge the divide between technological capabilities and pedagogical practices in this rapidly evolving domain. It will provide a comprehensive view of how AI is not just enhancing, but potentially revolutionizing the landscape of personalized learning, offering new paradigms for education that previous reviews have not fully explored.

METHOD

A methodical and descriptive approach to examine the existing literature was adopted, following the guidelines outlined by Okoli and Schabram (2010) and following the guidelines of the PRISMA statement. This approach facilitated a thorough process encompassing identification, screening, eligibility assessment, and source analysis. Adherence to these well-established procedures was instrumental in achieving a comprehensive and targeted identification of pertinent publications from the extensive body of available literature. The systematic steps of the review process are visually presented in **Figure 2**, outlining the methodological stages conducted following recommended best practices for scholarly literature reviews.

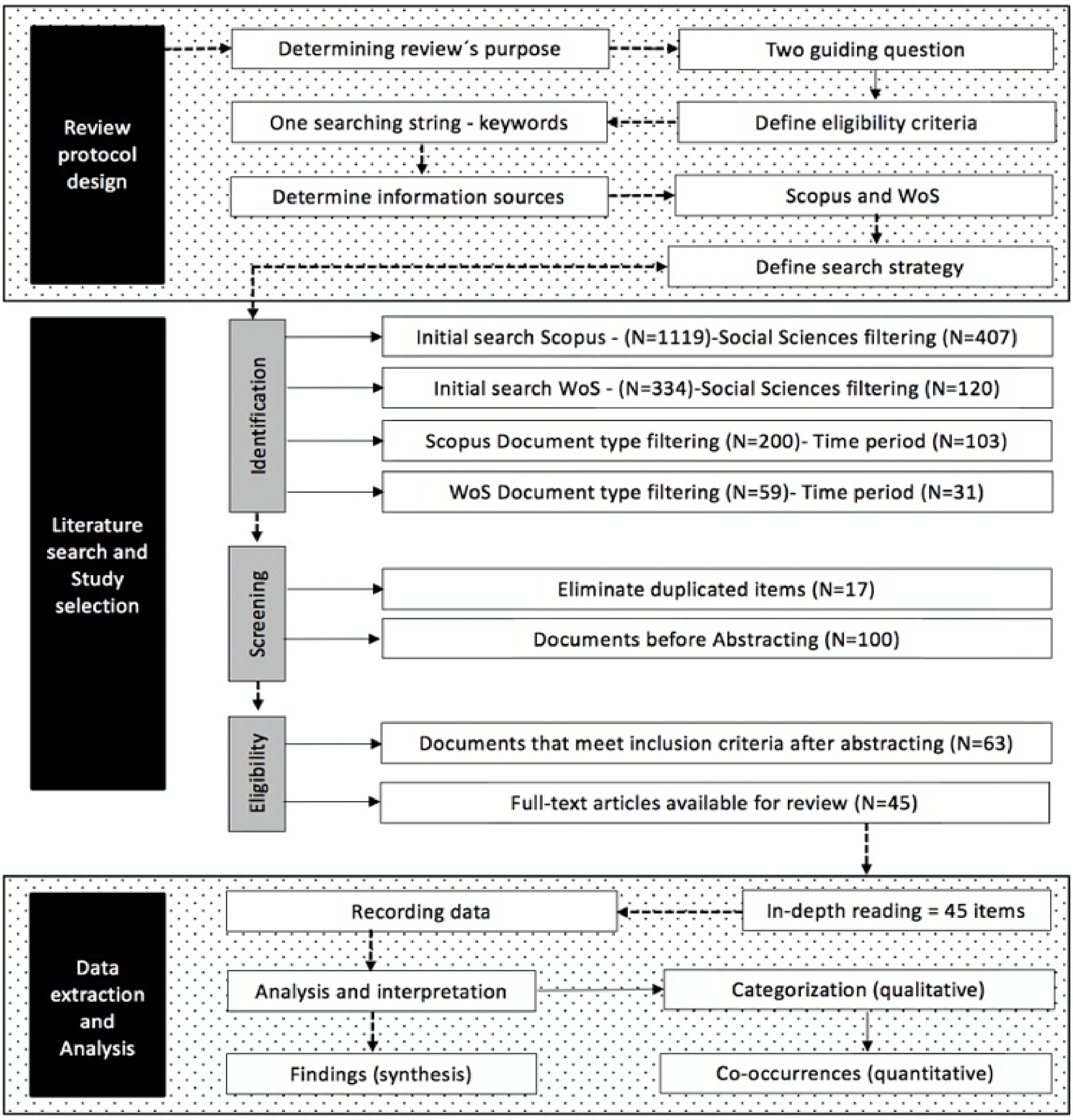

Figure 2. Review method design (Source: Authors' own elaboration)

Review Protocol Design

The initial phase of the literature review focused on establishing its purpose, which aimed to identify the platforms and software utilized for facilitating or endorsing personalized learning. To guide this review, a specific research question was crafted: What platforms and software have been employed to facilitate or support personalized learning processes?

After formulating the research question, the next step entailed the selection of suitable sources for consultation. Scopus and Web of Science (WoS), two comprehensive journal databases renowned for their stringent review and editorial processes, were chosen due to their extensive coverage and the diversity of journals they encompass. To address the research inquiry, a single keyword string was employed in both Scopus and WoS, incorporating the following terms:

- `TITLE-ABS-KEY ("personalized learning" AND (platforms OR software))`

Literature Searching and Study Selection

The process of searching and selecting the articles that would later be read in-depth and analyzed to extract relevant data to answer the review questions was conducted through filtering processes using the databases' tools. Thus, the first filter corresponded to the subject (Social Sciences), the second to the type of document (articles), and the last to the period (2019-2023). This was carried out in both Scopus and WoS, yielding the results shown in **Table 1**.

Table 1. Searching and filtering (Scopus and WoS)

Filter	Scopus	WoS
Initial searching	1,119	334
Social sciences	407	120
Type of document (article)	200	59
Period (2019-2023)	103	31
Eliminate 17 duplicated records	86	14
Total documents	100	
Documents after abstracting	63	
Documents available for reading	45	

The filtering process ended with a set of 100 documents, after eliminating 17 duplicate articles. These 100 documents went through an abstracting process in which the following inclusion and exclusion criteria were applied:

- Selecting only articles explicitly addressing the use of platforms or software to support personalized learning.
- Choosing only articles approaching the research topic from an educational perspective and presenting research findings.

After completing this process, 37 documents that did not meet the above criteria were removed, and only 45 were available in full text for in-depth reading.

Data Extraction and Analysis

The data extraction phase involved a meticulous examination of each selected article, with relevant information systematically recorded in a documentation matrix. In the context of a comprehensive review, the analysis of data necessitated the application of both qualitative and quantitative methodologies to ensure a holistic understanding of the research findings. This dual approach comprised two complementary processes: a qualitative analysis based on grouping or categorization, and a quantitative analysis rooted in frequency analysis. The integration of these methods facilitated a multifaceted examination of the data, allowing for a nuanced interpretation of the themes and patterns that emerged. Through this balanced analytical framework, the study aimed to provide a robust and insightful response to the research questions posed, leveraging the strengths of both qualitative richness and quantitative rigor.

The qualitative analysis began with extracting key findings, themes, and concepts discussed in each study. Following this, the data underwent a coding process that entailed assigning labels or tags to various pieces of information based on their content, thereby organizing the data into manageable categories.

Subsequently, through a thematic analysis, the coded data were examined to identify recurring themes or patterns. This involved grouping similar codes and recognizing the overarching themes that emerged from the data. Once themes were identified, the data were further categorized into broader groups in the categorization phase. Each category represented a specific aspect or dimension of the review questions.

Finally, the process culminated in the interpretation phase, where the categorized data were analyzed to draw meaningful insights and conclusions. This step involved understanding the relationships between different categories and how they contributed to answering the research questions.

In parallel, the quantitative analysis included the frequency calculation step, which involved determining the frequency of each variable or theme by counting the number of times each variable appeared across the dataset. To further analyze this frequency data, basic statistical methods were applied. This included calculating percentages, means, or distributions to comprehend the prevalence of different variables.

Consequently, the quantitative analysis yielded a clear depiction of the prevalence and distribution of various themes or variables within the data. This allowed for the identification of trends and patterns that could be quantified and compared, thereby complementing the qualitative findings.

The final phase of the review entailed the synthesis, interpretation, and compilation of the results into a cohesive narrative. The findings adhered to the IMRaD (Introduction, Methods, Results, and Discussion) format, facilitating a comprehensive comprehension of the research outcomes. During this stage, both qualitative and quantitative analyses were conducted, ensuring a rigorous assessment of the collected data. The research team painstakingly reviewed the data for accuracy and relevance, extracting crucial insights and identifying trends. Subsequently, the synthesized findings were interpreted to provide a deeper insight into the research subject. Ultimately, the researchers structured and presented the results systematically and logically, encompassing the methodology, findings, and subsequent discussions.

RESULTS

The data extracted from the reviewed studies enabled the identification of three major groups of outcomes related to platforms, software, or other digital developments supporting personalized learning processes. These categories were determined through an extensive process of thematic analysis and frequency analysis. Initially, the qualitative data were examined to identify recurring themes and concepts. This thematic analysis involved coding the data and grouping similar codes. Through this process, three primary categories emerged as the most significant in supporting personalized learning processes: Artificial Intelligence (39.0%), Platforms and Software (27.0%), and Learning Systems and E-learning (36.0%).

Artificial Intelligence

One of the most consistent findings throughout the review pertains to the pivotal role played by artificial intelligence in the consolidation and development of adaptive or personalized learning environments. Numerous studies support this perspective, such as Lhafra and Abdoun (2023), Arroub et al. (2020), Wang and Nie (2023) or Gligorea et al. (2023), focusing on the need to create specific scenarios, as proposed by Jo and Jun (2022). These studies delve into the perceptions of students and instructors regarding AI in personalized learning, revealing variations in the sentiments of both groups. Primary data were analyzed using Mann-Whitney and Kruskal-Wallis tests, underscoring the importance of carefully selecting technologies and establishing success criteria for the effective implementation of personalized learning practices.

Figure 3 shows the key terms most frequently presented in the reviewed studies, related to AI and later, the interpretation of these key terms is presented in the context of the guiding questions of the review.

AI in education holds significant potential for personalizing learning and democratizing education, as asserted by Al-Badi et al. (2022). Efforts are underway to implement globally AI-driven educational systems, intelligent agents, autonomous assessments, and student support chatbots. This aims to facilitate bidirectional communication between students and instructors, maximizing collaborative learning. In

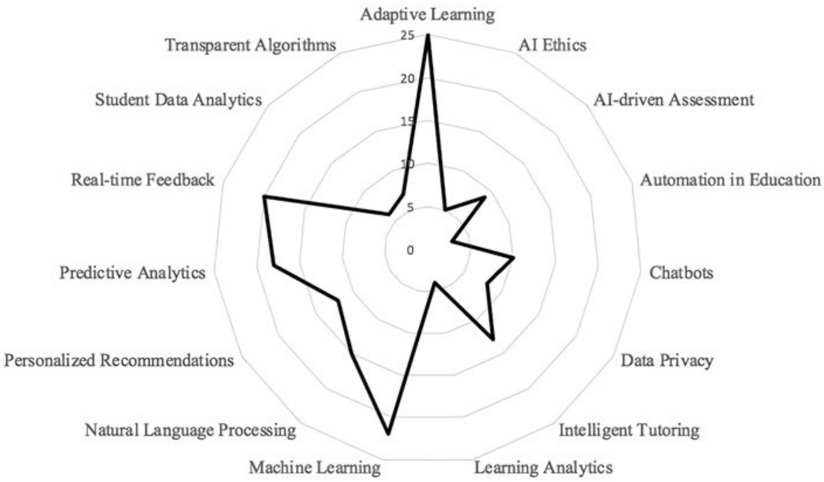

Figure 3. Most frequent AI-related key terms (Source: Authors' own elaboration)

alignment with these propositions, a study on a machine learning approach to personalize computerized cognitive training interventions (Vladisauskas et al., 2022) represents a preliminary step in anticipating the potential benefits of a cognitive training protocol based on participants' initial characteristics.

Cognitive training literature emphasizes the importance of AI and adaptive/personalized learning as a key paradigm in educational technology research, as reaffirmed by Xie et al. (2019), Chettaoui et al. (2021), Cheng et al. (2020) and Bethencourt-Aguilar et al. (2023). Furthermore, AI is revealed as a valuable tool for supporting personalized learning, where AI systems analyze learning patterns and offer personalized recommendations on more effective resources and activities for each student. Additionally, according to Dai and Ke (2022), AI has the potential to transform social interactions in educational contexts, addressing challenges such as inhibiting the development of simulation-based systems for all students.

In a complementary study, Embarak (2022) examines the use of explainable artificial intelligence (XAI) technologies and the Internet of Behavior (IoB) to create intelligent educational systems offering personalized and adaptive education. IoB significantly improved system response, advancing students' academic progress. This proposed paradigm can enhance the design and implementation of e-learning, remote systems, hybrid models, and the impact of intelligent virtual assistants, which evolved from conversational agents using AI and natural language processing to interact naturally and perform various tasks on Internet-connected devices (Alimamy & Kuhail, 2023; Borakati, 2021; Disa et al., 2022; Fragoso-Diaz et al., 2021).

Finally, results related to the use of artificial intelligence are linked to the importance of learning analytics as a key factor in achieving personalization in learning. According to Wong et al. (2023) and Huang et al. (2023), learning analytics are crucial when implementing personalization processes due to their ability to produce results about individuals' dynamics in school activities based on their generated data from online participation. Perhaps most notably, this result underscores the need to go beyond predictive analytics related to dropouts and incorporate them into teaching strategies.

Platforms and Software

Figure 4 shows the key terms most frequently presented in the reviewed studies, related to platforms and software and later, the interpretation of these key terms is presented in the context of the guiding questions of the review.

According to Alamri et al. (2021), Li et al. (2023), Harichandana et al. (2023), and Duan and Duan (2021), online platforms are integrated into learning environments to facilitate education, retention, and student engagement, and its usefulness is enhanced with the use of AI. Various platforms designed for massive open online courses (MOOCs), such as Udemy, Coursera, and edX, offer content personalization based on student needs.

However, managing both massiveness and personalization in MOOCs has proven more challenging than advancing, due to inadequate planning and insufficient consideration of human resources as an essential and

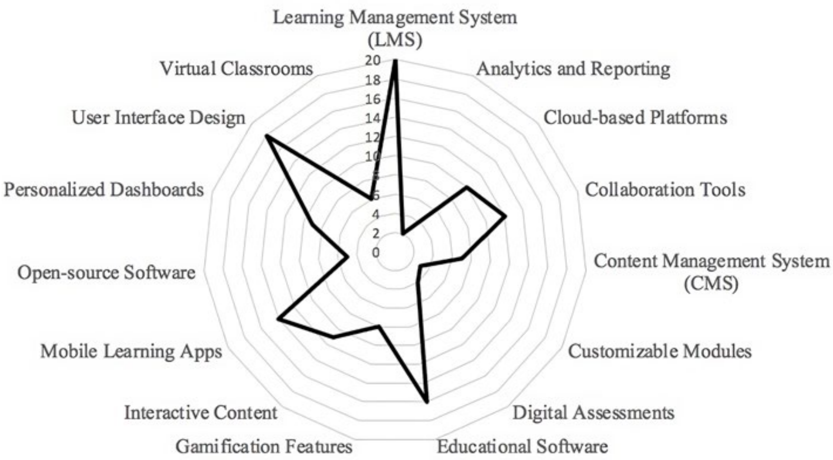

Figure 4. Most frequent platforms and software-related key terms (Source: Authors' own elaboration)

invaluable element, which is malleable, influential, and susceptible to changes in school contexts, as suggested by Chiappe et al. (2015).

Similar to MOOCs, LMS like Moodle and Blackboard allow educators to manage online courses. Additionally, authoring tools such as Articulate and Captivate facilitate the creation and customization of interactive content. Adaptive learning systems, such as DreamBox and Smart Sparrow, use AI to personalize content based on student progress, while online tutoring platforms, like Chegg and TutorMe, offer personalized assistance.

Within the implementation of these platforms, Lim et al. (2023), Margaryan et al. (2022), Du (2021), and Liu et al. (2022) highlight the importance of self-regulated learning (SRL) to enhance educational performance. This approach involves individuals taking primary responsibility for their learning, setting goals, and autonomously taking steps to achieve them. SRL is based on the premise that learning extends beyond the classroom and thrives on intrinsic motivation, goal-setting, self-assessment, reflection, time management, and learning organization.

From a similar perspective, the use of platforms, software, and personalized learning environments responds to student needs in the form of adaptive learning. This implies the ability of educational systems to adjust the pace and difficulty of content according to each student's individual needs. Adaptive learning prototypes include real-time assessments and personalized recommendations for content and activities. Despite potential terminology issues in educational scenarios, often expressing various terms for the same meaning, the personalization of learning environments in education arises from teachers' needs to address multicultural and diverse classrooms with students of various learning styles and rhythms, as emphasized by Zhao (2023).

Expanding on this, according to Alamri et al. (2021), technological models support personalization in blended learning environments in higher education. Studies based on the Internet of Things (IoT), computerized instructions, machine learning, and others, define and describe the theory and practice of personalized learning in higher education, under three emerging technological initiatives: open digital badges (Muilenburg & Berge, 2016; Piedra, 2021; Reed, 2023), competency-based learning technology (Jones-Schenk, 2014), and adaptable learning technology (Merikko & Kivimäki, 2022; Moltudal et al., 2020). These models guide the design of learning platforms that share student profiles and learning analytics, informing instructors about learning progress.

Another noteworthy example relates to the existence of portfolio management software to personalize learning in university environments. This initiative's results include conceptualization and expanding the field of theoretical knowledge related to the requirements that the system needs for its development (Eckell et al., 2020). It is essential to mention that in this study, personalized learning configured paths aiming to design higher education environments focused on planned and organized activities, enabling teachers to make decisions about teaching progress individually and select materials that drive significant advancements in each student's learning process.

In terms of the analysis and implementation of personalization parameters in the development of computer-based adaptive learning environments, Al-Chalabi and Hussein (2020) indicate two key types of parameters for achieving personalized learning. The first, pre-admission, includes the student's level of prior knowledge, their set goals, language preferences, learning style, connectivity, and geographic location conditions. The second key parameters, during ongoing sessions, encompass learning needs, motivation levels, individual working memory capacity, prevalent intelligence type, cognitive style, satisfaction or delight, self-efficacy, self-regulated learning, and feedback.

Learning Systems and E-Learning

Figure 5 shows the key terms most frequently presented in the reviewed studies, related to learning systems and e-learning and later, the interpretation of these key terms is presented in the context of the guiding questions of the review.

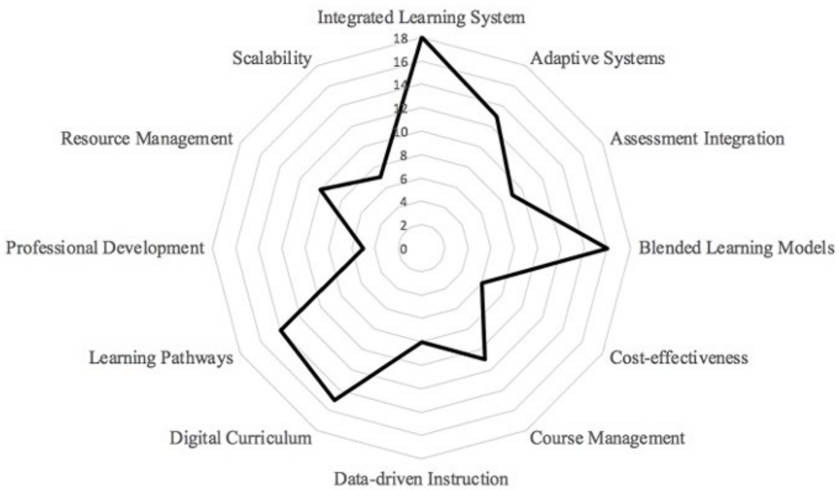

Figure 5. Most frequent learning systems and e-learning-related key terms (Source: Authors' own elaboration)

According to Voronina et al. (2021), a learning system refers to an organized set of processes, resources, tools, and activities designed to facilitate knowledge acquisition or the development of skills and abilities by an individual or a group.

Considering the above, some of the results obtained in this review highlight personalized learning as a crucial adaptive scenario to meet diverse educational needs in various dimensions. A significant paradigm shift is observed in student learning, requiring adaptation and customization for educational communities to acquire knowledge aligned with their interests (Engel Rocamora & Coll Salvador, 2021). In this context, hybrid teaching and learning environments stand out as optimal scenarios for promoting personalized learning. These scenarios encompass proposals guided by the teacher and focused on the student as a continuum of personalization, strengthening the sense students attribute to school learning (Cuban, 2018; Engel Rocamora & Coll Salvador, 2021; Fan & Meng, 2021).

As a consequence, digital technologies are beginning to be perceived as vehicles for creating learning environments that blur the boundaries between in-person and virtual settings (Engel Rocamora & Coll Salvador, 2021). Hybrid environments, more specifically, offer opportunities to design personalized strategies and coordinate actions between teachers and students effectively.

Furthermore, the importance of learning systems based on the construction and strengthening of personal learning environments (PLE) is highlighted. PLEs prioritize authentic learning developed in real and close contexts to the student (Berbel Gimenez & Borras-Gene, 2023; Bruen & Erdocia, 2024; Moltudal et al., 2022; Sun et al., 2023; Xu et al., 2024). In this regard, research on PLE emphasizes the importance of thematic analysis to identify and interpret personalized environments.

Additionally, the adaptation of learning styles and management tools seeks to personalize content according to the pace, style, and needs of the student (Álvarez-Torres et al., 2021; Torres-Gordillo & Herrero-Vázquez, 2017). Likewise, there are relevant studies in this same line proposing a system that allows social robots to identify new users and actively create a profile for personalized interaction between humans and robots. This system uses computer vision and human-robot interaction techniques to recognize users, retrieve their information, and adapt the robot's behavior based on user characteristics (Maroto-Gómez et al., 2023).

Other studies, such as Alamri et al. (2021) and Wong et al. (2023), converge on integrating pedagogical topics into technological or e-learning environments to facilitate student retention and engagement. The implementation of personalized learning takes place through platforms, software, and machine learning, revealing flexible forms of support for individual student needs and preferences.

By their way, Engel Rocamora and Coll Salvador (2021) indicate that the personalization of learning and the use of hybrid environments emerge as proposals to articulate virtual and traditional advances, centered on the student. In this scenario, learning is encouraged through online systems to promote student autonomy, although the difficulty in personalizing feedback in hybrid systems is recognized (Castro Sánchez, 2021; Ingkavara et al., 2022).

Other review results focus on gamification as a key element in learning systems seeking personalized learning, incorporating game elements into the learning process (Khaldi et al., 2023; Koravuna & Surepally, 2020; Tan et al., 2020; Yeşilçınar, 2023). Despite its potential, high dropout rates in digital learning environments underscore the need to address students' lack of motivation and engagement as key research elements.

Similarly, personalized learning has been explored in the context of learning systems based on the application of universal design for learning (UDL) principles. In this regard, Zhang et al. (2022) and Awwad (2023) found that developing and validating a self-report instrument for students could be used to measure whether a learning environment supports students' personalized learning experiences in middle and high schools, all according to the UDL framework.

Finally, a last element to highlight in personalized learning is addressed in the studies by Chaipidech et al. (2022), Shin (2022) and Kajonmanee et al. (2020) who investigated the effects of designing an integrated personalized learning system in technological pedagogical content knowledge (TPACK) of in-service teachers. The results indicated that in-service teachers significantly improved their abilities to personalize their students' learning when they could strengthen the knowledge articulating the dimensions that make up TPACK.

DISCUSSION AND CONCLUSIONS

In the contemporary educational landscape, the combination of technology and pedagogy has given rise to personalized learning paradigms, which have allowed consistent steps toward the remodeling of the traditional classroom experience. This comprehensive review revealed some practical implications and outlined possible future research trajectories emerging from the nuanced findings in artificial intelligence, platforms and software, and learning systems in the context of personalized learning.

Artificial Intelligence: Pioneering Personalization

Artificial intelligence emerges as the axis in the orchestration of adaptive learning environments. In this sense, the integration of AI in education not only highlights its fundamental role in the sense of process automation but also unravels a network of possibilities for the transformation of educational practices. As noted by Al-Badi et al. (2022), AI is very promising when it comes to democratizing education by personalizing learning experiences worldwide and in that sense, progress is being made in the implementation of different initiatives, among which intelligent agents and autonomous assessments stand out.

Considering the above, the practical implications of incorporating AI into personalized learning environments are profound. In this regard, it can be said that the careful selection of AI technologies and the definition of success criteria are imperative for their adequate educational integration. As mentioned by Xie et al. (2019), AI's ability to analyze learning patterns and offer personalized recommendations highlights its potential to revolutionize the educational landscape, in the sense of forming more adaptive and personalized learning experiences.

However, future research should examine the long-term impact of AI-powered systems on student performance and engagement, analyzing the ethical considerations and potential biases inherent in these systems. Furthermore, evaluations of scalability and adaptability in various educational contexts are vital to ensure inclusive implementation. In this sense, Li et al. (2022) suggest that investigating the semantic nuances of AI-powered personalized learning in different cultural and linguistic contexts can help refine these systems for broader applicability.

Platforms and Software: A Catalyst for Engagement

Online platforms and software are emerging as dynamic catalysts driving personalized learning into the digital realm. From MOOCs to LMS and adaptive learning systems, the diverse range of tools seems to meet the educational needs of an ever-changing world. However, as Alamri et al. (2021) mention, the management of massiveness and personalization within online platforms pose multiple challenges, emphasizing the need for meticulous planning and the recognition of human resources as invaluable components.

The practical implications of efficiently integrating online platforms into educational environments are multifaceted. Available research in this area indicates that these platforms have the potential to improve retention and engagement by offering personalized content based on student needs. Additionally, such adaptive learning systems, through real-time assessments and personalized recommendations, offer personalized support, as exemplified by the studies on DreamBox and Smart Sparrow. On the other hand, in this context, the incorporation of SRL principles, as highlighted by Lim et al. (2023), is crucial to reinforce educational performance in personalized learning environments.

Future research in this area should focus on the effectiveness of MOOCs and LMS in accommodating diverse learning styles and preferences. Investigating the long-term impacts of SRL principles in personalized learning contexts would prove crucial for a nuanced and deeper understanding of its sustained benefits. Additionally, exploring the role of platforms and software in promoting equity in education and bridging the digital divide is an avenue worthy of further investigation.

Learning Systems: Orchestrating Authenticity

Learning systems, which include processes, resources, and tools, form the basis of personalized learning, which is among the structural elements that are promoting a paradigm shift towards hybrid teaching and learning environments with great potential to coordinate and execute strategies. Efficiently personalized. In this context, the emphasis on personal learning environments accentuates the importance of authentic learning in real contexts, as proposed by Moltudal et al. (2022).

Considering the above, hybrid environments, when they foster effective coordination between teachers and students, present optimal scenarios to promote personalized learning. If the infusion of gamification elements is added to this, commitment and motivation within learning systems are amplified, as indicated by studies such as that of Khaldi et al. (2023). Furthermore, if the application of the principles of UDL is added to the above, it ends up providing a very effective framework to measure and support personalized learning experiences, as noted by Zhang et al. (2022).

According to Alzahrani and Alhalafawy (2023), gamification, while promising, poses challenges such as high dropout rates in digital learning environments, therefore, future research should delve into the sustained effects of gamification in reducing school dropout rates and maintaining student motivation, which requires longitudinal studies for a comprehensive understanding of its impact. Furthermore, further validation of instruments to measure personalized learning experiences within the UDL framework is essential to refine pedagogical practices and ensure inclusive education, which is an issue related to personalization.

As a conclusion produced by this review, it is worth mentioning that the integration of practical implications and future research directions in personalized learning contexts requires a nuanced understanding of the intricate interaction between AI, platforms, and learning systems. By recognizing these nuances, educators, policymakers, and researchers can collectively harness the transformative potential inherent in personalized learning paradigms, paving the way for an educational landscape that is not only adaptive but also authentically aligned with the needs and preferences of diverse students.

In other words, the collective findings of this review underscore the transformative potential of artificial intelligence in the field of personalized learning. AI, along with educational platforms and software, integrated learning systems, and e-learning, plays a pivotal role in driving individualized educational experiences. The analysis reveals how AI technologies, in particular, enhance the personalization of educational content, adapting to diverse learner needs and significantly improving engagement and efficacy. By systematically categorizing and analyzing the data, this review advances our understanding of AI's specific contributions to personalized learning, providing a robust framework for future research and practical applications. The synthesis of qualitative and quantitative analyses highlights the critical role of AI in creating tailored educational pathways, suggesting that the integration of AI technologies is essential for a holistic approach to personalized education. These insights offer valuable guidance for educators, policymakers, and developers aiming to leverage AI to foster more effective and inclusive learning environments. This review not only consolidates existing knowledge but also paves the way for future innovations in the application of AI in education, reinforcing the necessity of continued exploration and development in this dynamic and evolving field.

Thus, the dynamic interplay between AI, learning platforms, and systems offers a mosaic of opportunities for the evolution of personalized learning, emphasizing the importance of continuous exploration and refinement in this ever-evolving educational landscape.

Recommendations and Limitations

The implications of these findings for educational practitioners are profound. Educators and instructional designers should incorporate AI-driven tools to tailor learning experiences. For instance, adaptive learning platforms can adjust the difficulty of tasks based on real-time student performance data. Additionally, teachers can leverage data analytics to gain insights into student progress and identify areas needing intervention, thereby allowing for timely and targeted support. Moreover, the implementation of AI technologies such as chatbots and virtual tutors can provide instant feedback and support, making learning more interactive and engaging. Instructional designers should also focus on developing curricula that leverage AI to offer personalized learning paths, ensuring that each student can progress at their own pace. Furthermore, AI can facilitate collaborative learning by forming groups based on students' strengths and weaknesses, promoting peer-to-peer learning and support.

However, despite the promising findings, some limitations within the reviewed studies and the review process itself must be acknowledged. Many reviewed studies relied on small sample sizes, which may limit the generalizability of the results. The same limitation applies to the final review sample, thus, a replication of this review with a wider sample could provide new insights and perspectives on AI´s integration in Education as an evolving object of study. Additionally, the rapid evolution of AI technologies means that some findings may quickly become outdated as innovations emerge. Methodological weaknesses, such as a lack of longitudinal studies, also impact the ability to assess the long-term effects of AI in personalized learning. Furthermore, there is a need for more comprehensive research that includes diverse educational settings and populations to enhance the applicability of the findings across different contexts.

In conclusion, while AI's role in personalized learning holds significant promise, it is essential for future research to address these limitations by incorporating larger, more diverse samples and employing robust, longitudinal methodologies. Educators and policymakers should remain cautious yet optimistic, continually adapting and refining AI applications in education based on ongoing research and practical feedback. By embracing AI's capabilities while acknowledging and addressing its current limitations, the field of personalized learning can continue to evolve, offering increasingly effective and inclusive educational experiences. This review not only consolidates existing knowledge but also paves the way for future innovations in the application of AI in education, reinforcing the necessity of continued exploration and development in this dynamic and evolving field.

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REFERENCES

Alamri, H. A., Watson, S., & Watson, W. (2021). Learning technology models that support personalization within blended learning environments in higher education. *TechTrends, 65*(1), 62–78. https://doi.org/10.1007/s11528-020-00530-3

Al-Badi, A., Khan, A., & Eid-Alotaibi. (2022). Perceptions of learners and instructors towards artificial intelligence in personalized learning. *Procedia Computer Science, 201*, 445–451. https://doi.org/10.1016/j.procs.2022.03.058

Al-Chalabi, H. K. M., & Hussein, A. M. (2020). Analysis & implementation of personalisation parameters in the development of computer-based adaptive learning environment. *SAR Journal–Science and Research Journal, 3*(1), 3–9. https://doi.org/10.18421//SAR31-01

Ali, A. (2023). Exploring the transformative potential of technology in overcoming educational disparities. *International Journal of Multidisciplinary Sciences and Arts, 2*(1), 107–117. https://doi.org/10.47709/ijmdsa.v2i1.2559

Alimamy, S., & Kuhail, M. A. (2023). I will be with you Alexa! The impact of intelligent virtual assistant's authenticity and personalization on user reusage intentions. *Computers in Human Behavior, 143*, Article 107711. https://doi.org/10.1016/j.chb.2023.107711

Álvarez-Torres, J. H., Cuatindioy-Imbachi, J., González-Palacio, L., Luna-del Risco, M. A., González-Palacio, M., & Aguirre-Morales, J. (2021). Antecedentes de los estilos de aprendizaje para entornos virtuales [Background of learning styles for virtual environments]. *Revista Lasallista de Investigación, 18*(1), 236–248. https://doi.org/10.22507/rli.v18n1a14

Alzahrani, F. K., & Alhalafawy, W. S. (2023). Gamification for learning sustainability in the blackboard system: Motivators and obstacles from faculty members' perspectives. *Sustainability, 15*(5), Article 4613. https://doi.org/10.3390/su15054613

Arroub, A., Hssina, B., & Douzi, K. (2020). An overview on the use of artificial intelligence in adaptive learning: Comparative study. In M. Ezziyyani (Ed.), *Advanced intelligent systems for sustainable development* (vol 1102, pp. 101–106). Springer International Publishing. https://doi.org/10.1007/978-3-030-36653-7_10

Awwad, A. M. A. (2023). A universal design for an adaptive context-aware mobile cloud learning framework using machine learning. *Journal of Mobile Multimedia, 19*(3), 707–738. https://doi.org/10.13052/jmm1550-4646.1934

Babu, G., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences, 13*(9), Article 196. https://doi.org/10.3390/admsci13090196

Berbel Gimenez, G., & Borras-Gene, O. (2023). Effects of a personal learning environment approach in a master's program for future teachers. *Education Sciences, 13*(11), Article 1129. https://doi.org/10.3390/educsci13111129

Bethencourt-Aguilar, A., Castellanos-Nieves, D., Sosa-Alonso, J. J., & Area-Moreira, M. (2023). Use of generative adversarial networks (GANs) in educational technology research. *Journal of New Approaches in Educational Research, 12*(1), Article 153. https://doi.org/10.7821/naer.2023.1.1231

Borakati, A. (2021). Evaluation of an international medical e-learning course with natural language processing and machine learning. *BMC Medical Education, 21*(1), Article 181. https://doi.org/10.1186/s12909-021-02609-8

Bruen, J., & Erdocia, I. (2024). Formal and informal foreign language learning at university: Blurring the boundaries. *The Language Learning Journal*. https://doi.org/10.1080/09571736.2024.2306157

Bura, A., Joshi, S., Deshpande, S., Chaudhari, R., & Deshpande, K. (2023). ML based comprehensive application to enhance soft skills. In *Proceedings 11th International Conference on Emerging Trends in Engineering & Technology–Signal and Information Processing* (pp. 1–6). https://doi.org/10.1109/ICETET-SIP58143.2023.10151569

Castro Sánchez, M. (2021). El dispositivo TUYA como estrategia de personalización en educación en línea [The TUYA device as a personalization strategy in online education]. *Austral Comunicación, 10*(02), e9–e23. https://doi.org/10.26422/aucom.2021.1002.cas

Chaipidech, P., Srisawasdi, N., Kajornmanee, T., & Chaipah, K. (2022). A personalized learning system-supported professional training model for teachers' TPACK development. *Computers and Education: Artificial Intelligence, 3*, Article 100064. https://doi.org/10.1016/j.caeai.2022.100064

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cheng, X., Sun, J., & Zarifis, A. (2020). Artificial intelligence and deep learning in educational technology research and practice. *British Journal of Educational Technology, 51*(5), 1653–1656. https://doi.org/10.1111/bjet.13018

Chettaoui, N., Atia, A., & Bouhlel, M. S. (2021). Predicting student performance in an embodied learning environment. In *Proceedings of the International Mobile, Intelligent, and Ubiquitous Computing Conference* (pp. 1–7). https://doi.org/10.1109/MIUCC52538.2021.9447603

Chiappe, A., Hine, N., & Martínez-Silva, J. A. (2015). Literature and practice: A critical review of MOOCs. *Comunicar, 22*(44), 09–18. https://doi.org/10.3916/C44-2015-01

Cuban, L. (2018). *The flight of a butterfly or the path of a bullet? Using technology to transform teaching and learning*. Harvard Education Press.

Dai, C.-P., & Ke, F. (2022). Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review. *Computers and Education: Artificial Intelligence, 3*, Article 100087. https://doi.org/10.1016/j.caeai.2022.100087

Disa, S., Purnamawati, & Idkhan, A. M. (2022). Web e-learning: Automated essay assessment based on natural language processing using vector space model. In *Proceedings of the 4th International Conference on Cybernetics and Intelligent System* (pp. 1–4). https://doi.org/10.1109/ICORIS56080.2022.10031317

Du, M. (2021). Self-regulated learning model in SPOC of blended learning based on online education platform. In *Proceedings of the 2nd International Conference on Information Science and Education* (pp. 1245–1248). https://doi.org/10.1109/ICISE-IE53922.2021.00279

Duan, X., & Duan, P. (2021). English education online platform based on artificial intelligence. In *Proceedings of the International Conference on Aviation Safety and Information Technology* (pp. 87–90). https://doi.org/10.1145/3510858.3510895

Eckell, N., Santucci, V., & Romero, L. (2020). Design of a portfolio management software to personalize learning in university environments. *Latin-American Journal of Computing, 7*(1), 114–137.

Embarak, O. H. (2022). Internet of behaviour (IoB)-based AI models for personalized smart education systems. *Procedia Computer Science, 203*, 103–110. https://doi.org/10.1016/j.procs.2022.07.015

Engel Rocamora, A., & Coll Salvador, C. (2021). Entornos híbridos de enseñanza y aprendizaje para promover la personalización del aprendizaje [Hybrid teaching and learning environments to promote personalized learning]. *Revista Iberoamericana de Educación a Distancia, 25*(1). https://doi.org/10.5944/ried.25.1.31489

Fan, G., & Meng, F. (2021). Personalized recommendation algorithm for curriculum- and politics-oriented hybrid teaching resources. In *Proceedings of the IEEE International Conference on Industrial Application of Artificial Intelligence* (pp. 361–366). https://doi.org/10.1109/IAAI54625.2021.9699911

Fragoso-Diaz, O., Lopez Caballero, V., Rojas-Perez, J. C., Santaolaya-Salgado, R., & Gonzalez-Serna, J. G. (2021). On the generation of e-learning resources using business process, natural language processing, and web services. *IT Professional, 23*(2), 40–44. https://doi.org/10.1109/MITP.2021.3054640

Ghiasabadi Farahani, M., Akbari Torkestani, J., & Rahmani, M. (2022). Adaptive personalized recommender system using learning automata and items clustering. *Information Systems, 106*, Article 101978. https://doi.org/10.1016/j.is.2021.101978

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive learning using artificial intelligence in e-learning: A literature review. *Education Sciences, 13*(12), Article 1216. https://doi.org/10.3390/educsci13121216

Gong, W. (2022). Reshaping the EFL formative assessment pedagogy with blockchain technology. *International Journal of English Linguistics, 13*(1), Article 12. https://doi.org/10.5539/ijel.v13n1p12

Harichandana, B., Misra, S., Nagendra, K. V., & Anandaraj, S. (2023). Introduction of virtual environment with personalized content recommendation for realistic avatar creation in online platform using machine learning. In *Proceedings of the 2nd International Conference on Augmented Intelligence and Sustainable Systems* (pp. 540–545). https://doi.org/10.1109/ICAISS58487.2023.10250673

Hernandez-Cardenas, L. S., Castano, L., Cruz Guzman, C., & Nigenda Alvarez, J. P. (2022). Personalised learning model for academic leveling and improvement in higher education. *Australasian Journal of Educational Technology, 38*(2), 70–82. https://doi.org/10.14742/ajet.7084

Huang, A. Y. Q., Lu, O. H. T., & Yang, S. J. H. (2023). Effects of artificial intelligence–enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers & Education, 194*, Article 104684. https://doi.org/10.1016/j.compedu.2022.104684

Hui, B. (2023). A personalized learning approach to support students with diverse academic backgrounds. In *Proceedings of the IEEE Frontiers in Education Conference* (pp. 1–9). https://doi.org/10.1109/FIE58773.2023.10343070

Ibrohim, I., Kusumaningrum, I. K., Hamimi, E., Putra, W. E., Utomo, J., Kundariati, M., Hajar, M. U., & Bin Nik Malek, N. A. N. (2023). Science students' literacy and faculty members' perspective toward nanotechnology: Is it needed in 21st century education? *Eurasia Journal of Mathematics, Science and Technology Education, 19*(12), Article em2362. https://doi.org/10.29333/ejmste/13835

Ingkavara, T., Panjaburee, P., Srisawasdi, N., & Sajjapanroj, S. (2022). The use of a personalized learning approach to implementing self-regulated online learning. *Computers and Education: Artificial Intelligence, 3*, Article 100086. https://doi.org/10.1016/j.caeai.2022.100086

Jo, H., & Jun, C.-H. (2022). A personalized classification model using similarity learning via supervised autoencoder. *Applied Soft Computing, 131*, Article 109773. https://doi.org/10.1016/j.asoc.2022.109773

Jones-Schenk, J. (2014). Nursing education at Western Governors University: A modern, disruptive approach. *Journal of Professional Nursing, 30*(2), 168–174. https://doi.org/10.1016/j.profnurs.2013.09.005

Jun, W., Iqbal, M. S., Abbasi, R., Omar, M., & Huiqin, C. (2024). Web-semantic-driven machine learning and blockchain for transformative change in the future of physical education. *International Journal on Semantic Web and Information Systems, 20*(1), 1–16. https://doi.org/10.4018/IJSWIS.337961

Kajonmanee, T., Chaipidech, P., Srisawasdi, N., & Chaipah, K. (2020). A personalised mobile learning system for promoting STEM discipline teachers' TPACK development. *International Journal of Mobile Learning and Organisation, 14*(2), Article 215. https://doi.org/10.1504/IJMLO.2020.106186

Kaur, K. (2021). Role of artificial intelligence in education: Peninsula College Central Malaysia. *International Journal of Academic Research in Progressive Education and Development, 10*(2), 1006–1016. https://doi.org/10.6007/IJARPED/v10-i1/8641

Khaldi, A., Bouzidi, R., & Nader, F. (2023). Gamification of e-learning in higher education: A systematic literature review. *Smart Learning Environments, 10*(1), Article 10. https://doi.org/10.1186/s40561-023-00227-z

Koravuna, S., & Surepally, U. K. (2020). Educational gamification and artificial intelligence for promoting digital literacy. In *Proceedings of the 2nd International Conference on Intelligent and Innovative Computing Applications* (pp. 1–6). https://doi.org/10.1145/3415088.3415107

Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O. M. D., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability, 13*(18), Article 10424. https://doi.org/10.3390/su131810424

Kumar Tyagi, P., Singh, A. K., Tyagi, P., Kumar Chanchal, H., Gautam, P., & Nibhoria, S. (2023). Human-centred artificial intelligence in education, present and future opportunities. In *Proceedings of the 3rd International Conference on Advance Computing and Innovative Technologies in Engineering* (pp. 2742–2746). https://doi.org/10.1109/ICACITE57410.2023.10182545

Lhafra, F. Z., & Abdoun, O. (2023). Towards an adaptive learning process using artificial intelligence technologies. In S. Motahhir, & B. Bossoufi (Eds.), *Digital technologies and applications* (vol. 668, pp. 23–32). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-29857-8_3

Li, C.-C., Dong, Y., Liang, H., Pedrycz, W., & Herrera, F. (2022). Data-driven method to learning personalized individual semantics to support linguistic multi-attribute decision making. *Omega, 111*, Article 102642. https://doi.org/10.1016/j.omega.2022.102642

Li, J., Ouyang, J., Liu, J., Zhang, F., Wang, Z., Guo, X., Liu, M., & Taylor, D. (2023). Artificial intelligence-based online platform assists blood cell morphology learning: A mixed-methods sequential explanatory designed research. *Medical Teacher, 45*(6), 596–603. https://doi.org/10.1080/0142159X.2023.2190483

Lim, L., Bannert, M., Van Der Graaf, J., Singh, S., Fan, Y., Surendrannair, S., Rakovic, M., Molenaar, I., Moore, J., & Gašević, D. (2023). Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior, 139*, Article 107547. https://doi.org/10.1016/j.chb.2022.107547

Liu, S., Chen, Y., Huang, H., Xiao, L., & Hei, X. (2018). Towards smart educational recommendations with reinforcement learning in classroom. In *Proceedings of the IEEE International Conference on Teaching, Assessment, and Learning for Engineering* (pp. 1079–1084). https://doi.org/10.1109/TALE.2018.8615217

Liu, Y., Wen, W., Gao, Y., Zhang, X., Qu, T., Yin, D., Peng, X., & Shi, Y. (2022). Online homework intelligent platform based on self-regulated learning (SRL): Essential for sustainable development of online higher education. *Sustainability, 14*(24), Article 16904. https://doi.org/10.3390/su142416904

Margaryan, A., Albert, J., & Charlton-Czaplicki, T. (2022). Workplace learning in Crowdwork Questionnaire (WLCQ): Measuring self-regulated learning and skill development in online platform work. *International Journal of Training and Development, 26*(3), 495–515. https://doi.org/10.1111/ijtd.12268

Maroto-Gómez, M., Marqués-Villaroya, S., Castillo, J. C., Castro-González, Á., & Malfaz, M. (2023). Active learning based on computer vision and human-robot interaction for the user profiling and behavior personalization of an autonomous social robot. *Engineering Applications of Artificial Intelligence, 117*, Article 105631. https://doi.org/10.1016/j.engappai.2022.105631

Marzal, M.-Á., & Vivarelli, M. (2024). Convergence of artificial intelligence and digital skills: A necessary space for digital education and Education 4.0. *JLIS.it, 15*(1), 1–15. https://doi.org/10.36253/jlis.it-566

Merikko, J., & Kivimäki, V. (2022). "Replacing teachers? Doubt it." Practitioners' views on adaptive learning technologies' impact on the teaching profession. *Frontiers in Education, 7*, Article 1010255. https://doi.org/10.3389/feduc.2022.1010255

Moltudal, S. H., Krumsvik, R. J., & Høydal, K. L. (2022). Adaptive learning technology in primary education: Implications for professional teacher knowledge and classroom management. *Frontiers in Education, 7*, Article 830536. https://doi.org/10.3389/feduc.2022.830536

Moltudal, S., Høydal, K., & Krumsvik, R. J. (2020). Glimpses into real-life introduction of adaptive learning technology: A mixed methods research approach to personalised pupil learning. *Designs for Learning, 12*(1), 13–28. https://doi.org/10.16993/dfl.138

Muar, J. (2019). Educator's readiness for 21st century education. *Higher Education, 2015*, 2025.

Muilenburg, L. Y., & Berge, Z. L. (Eds.). (2016). *Digital badges in education*. Routledge. https://doi.org/10.4324/9781315718569

Nayan, N., Khalid, N. H. M., Mahat, H., Hashim, M., Saleh, Y., Kurniawan, E., & Khotimah, N. (2024). Understanding the element of 21st century education among teachers in Malaysia. *AIP Conference Proceedings, 2799*, Article 020117. https://doi.org/10.1063/5.0181875

Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B.-P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies, 28*(4), 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

Okoli, C., & Schabram, K. (2010). A guide to conducting a systematic literature review of information systems research. *Sprouts: Working Papers on Information Systems, 10*(26), 1–51. https://doi.org/10.2139/ssrn.1954824

Piedra, D. (2021). Open digital badges: The future of skill validation and credentialing. In J. Keengwe (Ed.), *Advances in educational technologies and instructional design* (pp. 1–14). IGI Global. https://doi.org/10.4018/978-1-7998-4360-3.ch001

Pokrivcakova, S. (2019). Preparing teachers for the application of AI-powered technologies in foreign language education. *Journal of Language and Cultural Education, 7*(3), 135–153. https://doi.org/10.2478/jolace-2019-0025

Ramírez Montoya, M. S., McGreal, R., & Obiageli Agbu, J.-F. (2022). Horizontes digitales complejos en el futuro de la educación 4.0: Luces desde las recomendaciones de UNESCO [Complex digital horizons in the future of education 4.0: Insights from UNESCO recommendations]. *Revista Iberoamericana de Educación a Distancia, 25*(2), 09–21. https://doi.org/10.5944/ried.25.2.33843

Reed, A. (2023). Micro-credentials and the role of evidence: Increasing the potential for learner-centeredness, inclusivity and an expansive model of assessment and credentialing. *The International Journal of Information and Learning Technology, 40*(5), 401–412. https://doi.org/10.1108/IJILT-12-2022-0228

Rienties, B., Køhler Simonsen, H., & Herodotou, C. (2020). Defining the boundaries between artificial intelligence in education, computer-supported collaborative learning, educational data mining, and learning analytics: A need for coherence. *Frontiers in Education, 5*, Article 128. https://doi.org/10.3389/feduc.2020.00128

Sharma, S., & Kumar, N. (2023). The future of education: Implications of artificial intelligence integration in learning environments. *International Journal of Enhanced Research in Educational Development, 11*(5), 129–133.

Shin, D. (2022). Teaching mathematics integrating intelligent tutoring systems: Investigating prospective teachers' concerns and TPACK. *International Journal of Science and Mathematics Education, 20*(8), 1659–1676. https://doi.org/10.1007/s10763-021-10221-x

Sun, Y., Xu, X., & Zhang, Y. (2023). Constructing guiding principles for the framework of culturally responsive pedagogy-guided personal learning environments in higher education. In *Proceedings of the 15th International Conference on Education Technology and Computers* (pp. 64–71). https://doi.org/10.1145/3629296.3629307

Swagatika, D., Sarmah Boruah, A., Sadhana, N., Dushyant, N., & Bajaj, K. K. (2023). Ethical considerations in using artificial intelligence to improve teaching and learning. *Tuijin Jishu/Journal of Propulsion Technology, 44*(4), 1031–1038. https://doi.org/10.52783/tjjpt.v44.i4.966

Tan, C. W., Ling, L., Yu, P.-D., Hang, C. N., & Wong, M. F. (2020). Mathematics gamification in mobile app software for personalized learning at scale. In *Proceedings of the IEEE Integrated STEM Education Conference* (pp. 1–5). https://doi.org/10.1109/ISEC49744.2020.9397846

Torres-Gordillo, J. J., & Herrero-Vázquez, E. A. (2017). PLE: Entorno personal de aprendizaje vs. entorno de aprendizaje personalizado [PLE: Personal learning environment vs. personalized learning environment]. *Revista Española de Orientación y Psicopedagogía, 27*(3), Article 26. https://doi.org/10.5944/reop.vol.27.num.3.2016.18798

Vhatkar, A., Pawar, V., Dash, S., Brahme, M., & Patil, L. (2023). Exploring the impact of AI and machine learning algorithms on engineering education: A comprehensive analysis of research articles in the Journal of Engineering Education. In *Proceedings of the 12th International Conference on System Modeling & Advancement in Research Trends* (pp. 449–453). https://doi.org/10.1109/SMART59791.2023.10428329

Vladisauskas, M., Belloli, L. M. L., Fernández Slezak, D., & Goldin, A. P. (2022). A machine learning approach to personalize computerized cognitive training interventions. *Frontiers in Artificial Intelligence, 5*, Article 788605. https://doi.org/10.3389/frai.2022.788605

Voronina, A., Shabalina, O., Kataev, A., & Sadovnikova, N. (2021). User engagement assessment for adaptive learning systems. In A. G. Kravets, M. Shcherbakov, D. Parygin, & P. P. Groumpos (Eds.), *Creativity in intelligent technologies and data science* (vol. 1448, pp. 545–558). Springer International Publishing. https://doi.org/10.1007/978-3-030-87034-8_40

Wang, L., & Nie, Z. (2023). Research on adaptive learning in K-12 education in the perspective of teachers' artificial intelligence literacy: Development; technology; improvement strategies. In *Proceedings of the 5th International Conference on Computer Science and Technologies in Education* (pp. 1–8). https://doi.org/10.1109/CSTE59648.2023.00059

Wong, B. T., Li, K. C., & Cheung, S. K. S. (2023). An analysis of learning analytics in personalised learning. *Journal of Computing in Higher Education, 35*(3), 371–390. https://doi.org/10.1007/s12528-022-09324-3

Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education, 140*, Article 103599. https://doi.org/10.1016/j.compedu.2019.103599

Xu, X., Wang, X., Zhang, Y., & Zheng, R. (2024). Applying ChatGPT to tackle the side effects of personal learning environments from learner and learning perspective: An interview of experts in higher education. *PLoS ONE, 19*(1), Article e0295646. https://doi.org/10.1371/journal.pone.0295646

Yeşilçınar, S. (2023). Personalized learning through gamification: A ChatGPT approach to English language learning. In G. Kartal (Ed.), *Advances in educational technologies and instructional design* (pp. 44–64). IGI Global. https://doi.org/10.4018/978-1-6684-9893-4.ch003

Zhang, L., Basham, J. D., & Carter, R. A. (2022). Measuring personalized learning through the lens of UDL: Development and content validation of a student self-report instrument. *Studies in Educational Evaluation, 72*, Article 101121. https://doi.org/10.1016/j.stueduc.2021.101121

Zhao, Y. (2023). Learning for uncertainty: Reach for greatness. *Educational Research for Policy and Practice*. https://doi.org/10.1007/s10671-023-09358-z