

From Uniformity to Uniqueness: Personalized Learning Through Artificial Intelligence

Camilo Aurelio Velandia-Rodríguez¹, Andrés Chiappe² & Angélica Vera Sagredo³

Abstract

This study systematically examines the evolution of personalized learning in education, focusing on the transformative potential of artificial intelligence (AI) in higher education. It aims to identify how AI addresses the barriers of traditional teacher-led and student-driven personalization methods, offering scalable and adaptive solutions to enhance individualized learning experiences. A systematic review was conducted using the Scopus database, analyzing 55 peer-reviewed published articles. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework guided the methodology, ensuring a rigorous approach to selecting and analyzing studies. Data extraction emphasized two guiding questions: the evolution of personalized learning and the methods employed to achieve it. Qualitative and quantitative analyses were employed to categorize findings and map trends over time. The review highlights a significant shift from traditional teacher-led models to technology-driven approaches in personalized learning. AI emerges as a pivotal tool, offering real-time data analysis, adaptive learning environments, and enhanced student autonomy. Despite challenges such as implementation costs and scalability, AI-driven personalization demonstrates the potential to overcome limitations in traditional education systems, particularly in higher education. This study uniquely bridges the gap between pedagogical approaches and technological advancements, showcasing AI's capability to revolutionize learning personalization. It provides actionable insights for educators and institutions aiming to implement effective, scalable, and inclusive educational strategies.

Keywords: *Artificial Intelligence; personalized learning; customized learning; individual instruction; higher education.*

Introduction

Education has undergone a transformative shift in recent decades, driven by digital technologies and accelerated by the COVID-19 pandemic (Deroncele-Acosta et al., 2023). From digital whiteboards to interactive platforms, these advancements have expanded access to learning and enhanced teacher-student interaction (Choudhury et al., 2015). However, as education becomes more interconnected, managing vast amounts of learning data has become a challenge. In this context, artificial intelligence (AI) is emerging as a key player (Kwon et al., 2023).

¹ Prof., Corporación Universitaria Minuto de Dios, Colombia; camilo.velandia@uniminuto.edu

² Dr., Universidad de La Sabana, Colombia; andres.chiappe@unisabana.edu.co (Corresponding author)

³ Dr. Universidad Católica de La Santísima Concepción, Chile; avera@ucsc.cl

AI refers to machines performing cognitive tasks such as reasoning, learning, and problem-solving. Through complex algorithms, AI can analyze and process large data volumes autonomously (Bartenev, 2022). In education, AI has been used to predict student dropout risks, but its potential extends further into learning personalization (Li & Wang, 2020).

Given these developments, the concept of personalized learning has gained increasing relevance within the framework of Education 4.0. This emerging paradigm integrates advanced technologies to foster intelligent, autonomous, and student-centered learning environments (León-Gómez et al., 2021). More specifically, Education 4.0 promotes adaptive learning experiences, real-time feedback, and data-driven instruction. Within this model, AI-powered personalization plays a key role by offering scalable and dynamic learning solutions that accommodate individual student needs. Nevertheless, despite its potential, significant research gaps remain, particularly concerning the effectiveness, equity, and ethical implications of AI-driven personalization in higher education. Furthermore, learning personalization is based on the principle that students learn differently and require tailored instructional approaches. Unlike traditional one-size-fits-all teaching methods, personalized learning adapts to individual needs, interests, and cognitive profiles (Makhambetova et al., 2021). Additionally, research suggests that effective personalization extends beyond content adaptation, as it also enhances motivation and engagement through customized learning pathways (Sun, 2016). For example, the use of AI-generated personalized study materials has shown promising results in improving academic performance and student engagement (Kucirkova et al., 2021).

To conceptualize personalized learning, different models have been proposed. On one hand, Rytivaara (2015) distinguishes between instructional adaptation and individualized student support. On the other hand, Makhambetova et al. (2021) emphasize the role of AI in fostering learner autonomy and self-regulation. These perspectives align with constructivist and connectivist learning theories, which highlight the importance of active, technology-mediated learning (Zheng et al., 2022). Moreover, as Information and Communication Technologies (ICTs) continue to expand, they further reinforce a global shift toward digital learning environments that prioritize personalization (Bolek et al., 2021).

However, despite these advancements, the implementation of personalized learning remains challenging. Traditional education models have struggled to keep pace with technological and societal changes. In this regard, Serres (2014) argues that rigid curriculum structures often hinder

true personalization, reducing it to superficial modifications rather than meaningful student-centred learning. Similarly, Costigan and Grey highlight that institutional constraints frequently limit the effectiveness of personalized learning strategies. In this sense, Velandia (2010) underscores that successful personalization requires greater flexibility in educational design. Therefore, overcoming these challenges demands a pedagogical rethinking, where educational institutions shift from standardized approaches toward context-sensitive, adaptive learning frameworks.

Over the past decade, various digital technologies have emerged as potential enablers of personalized learning, each contributing distinct mechanisms for adaptation and customization. Among the most widely explored solutions are Big Data analytics (Reidenberg & Schaub, 2018), learning analytics (Giannakos et al., 2016), adaptive learning (Fernández-Morante et al., 2021), Personal Learning Environments (Adell Segura & Castañeda Quintero, 2010), adaptive video games (Soflano et al., 2015), the MOOC (Chang et al., 2019) and semantic models (Iatrellis et al., 2019), whose investigative deployment is shown in Figure 1.

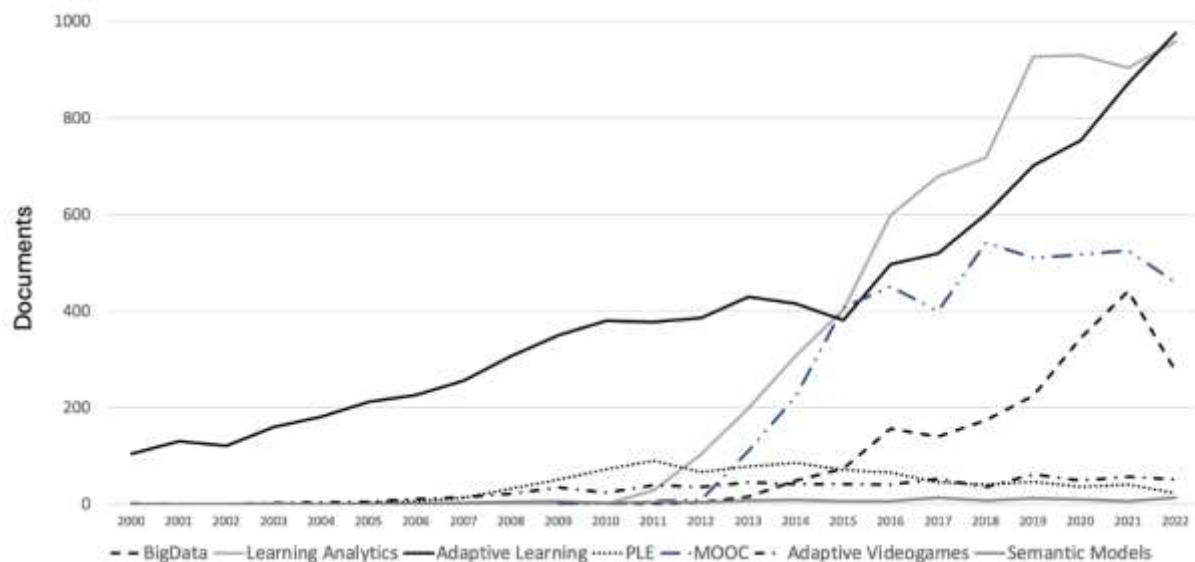


Figure 1. Technological alternatives to personalized learning

The increasing academic interest in AI-driven learning highlights its potential to transform education. However, widespread adoption of personalized learning remains limited in higher education (Ujir et al., 2020). The gap between technological advancements and real-world

implementation raises key questions about effectiveness and barriers. While case studies offer insights, a comprehensive understanding of AI-driven personalization is still lacking (Ridolfo et al., 2012). This study examines the evolution of personalized learning and explores pedagogical and technological implementation methods. Table 1 outlines the key differences between traditional and AI-driven personalization approaches, shedding light on their distinct advantages and challenges.

Table 1

Traditional vs. AI-driven Personalization Approaches (Mehendale, 2023)

Aspect	Traditional Personalization	AI-Driven Personalization
Method	Teacher-led differentiation	Algorithm-based adaptation
Data Use	Limited student data	Real-time data analysis
Feedback	Periodic assessment	Instant, personalized feedback
Adaptability	Fixed instructional plans	Dynamic, student-specific learning paths
Example Tools	Tutoring, adaptive tests	AI chatbots, recommendation engines

1.1 Theoretical Foundations of AI-Driven Personalized Learning

AI-driven personalized learning aligns with constructivist learning theories, emphasizing the learner's active role in constructing knowledge. Constructivism, developed by Piaget and expanded by Vygotsky, posits that learning occurs through experiences. AI supports this by dynamically adapting content, scaffolding learning, and facilitating self-regulated learning (Chen, 2024). Similarly, Connectivism, introduced by Siemens and Downes, views learning as occurring in distributed networks facilitated by technology (Ismail, 2024). AI exemplifies this by enabling students to engage with personalized content, fostering connections between knowledge domains and guiding them toward relevant resources using big data and predictive analytics.

1.2 Conceptual Model for AI-Personalized Learning

An AI-driven personalization model integrates three interconnected elements: AI as a mediator, student agency, and teacher intervention, ensuring adaptive, student-centered, and pedagogically sound learning experiences. AI serves as a dynamic mediator, adjusting learning pathways based on student performance, preferences, and needs. Through learning analytics and adaptive algorithms, AI identifies learning gaps, recommends resources, and optimizes instructional pacing.

Furthermore, AI enhances engagement by integrating gamified learning, intelligent tutoring systems, and real-time assessments. However, AI-driven mediation requires ethical safeguards to prevent algorithmic bias, misinterpretation of student needs, and over-standardization of learning pathways.

Despite AI's role, student agency remains essential. Learners should actively navigate and refine their learning pathways rather than passively following AI recommendations. Personalized dashboards and AI-powered Personal Learning Environments (PLEs) empower students to set goals, access adaptive resources, and track progress. Nevertheless, excessive reliance on AI risks diminishing critical thinking. To counter this, models must integrate mechanisms that foster self-regulation and independent decision-making.

Although AI enhances learning personalization, teacher intervention is irreplaceable. Educators contextualize AI recommendations, provide emotional support, and adapt instruction to individual needs. Furthermore, teachers mitigate AI biases, ensuring personalization does not reinforce inequalities. However, effective AI integration requires continuous teacher training in AI literacy and ethical oversight.

Ultimately, for AI-driven personalization to be truly effective, these three elements must work in harmony, ensuring AI enhances rather than dictates learning while preserving student autonomy and teacher expertise.

1.3 Challenges and Ethical Considerations in AI-Driven Personalization

Despite its benefits, AI-driven personalization presents ethical and implementation challenges. Algorithmic bias remains a key concern, as AI models trained on biased datasets can perpetuate inequalities (De Cremer et al., 2024). Ongoing auditing and diverse data integration are crucial to mitigate this. Additionally, the digital divide limits accessibility, restricting AI-driven benefits in under-resourced environments (Ujir et al., 2020). Ensuring inclusivity is necessary for equitable learning outcomes. Data privacy concerns also persist, as AI relies on extensive student data, necessitating privacy-preserving AI techniques and transparent policies (Reidenberg & Schaub, 2018). The literature indicates that personalized learning has evolved alongside technological advancements. However, gaps remain in understanding its long-term impact and identifying which approaches have been most effective. A deeper exploration of these conceptual and methodological changes is necessary to establish a clearer research agenda on AI-driven personalization.

1.4 Research Questions

In this context, the present study poses the following research questions, aimed at understanding both the historical evolution of learning personalization and the strategies employed in its application:

- How has the concept of learning personalization evolved over time?
- What methods or techniques have been used for learning personalization?

Method

The review was conducted based on the steps indicated by Moher et al. (2009, 2015) and Page et al. (2021), and following the main guidelines of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement, which are detailed in Figure 2.

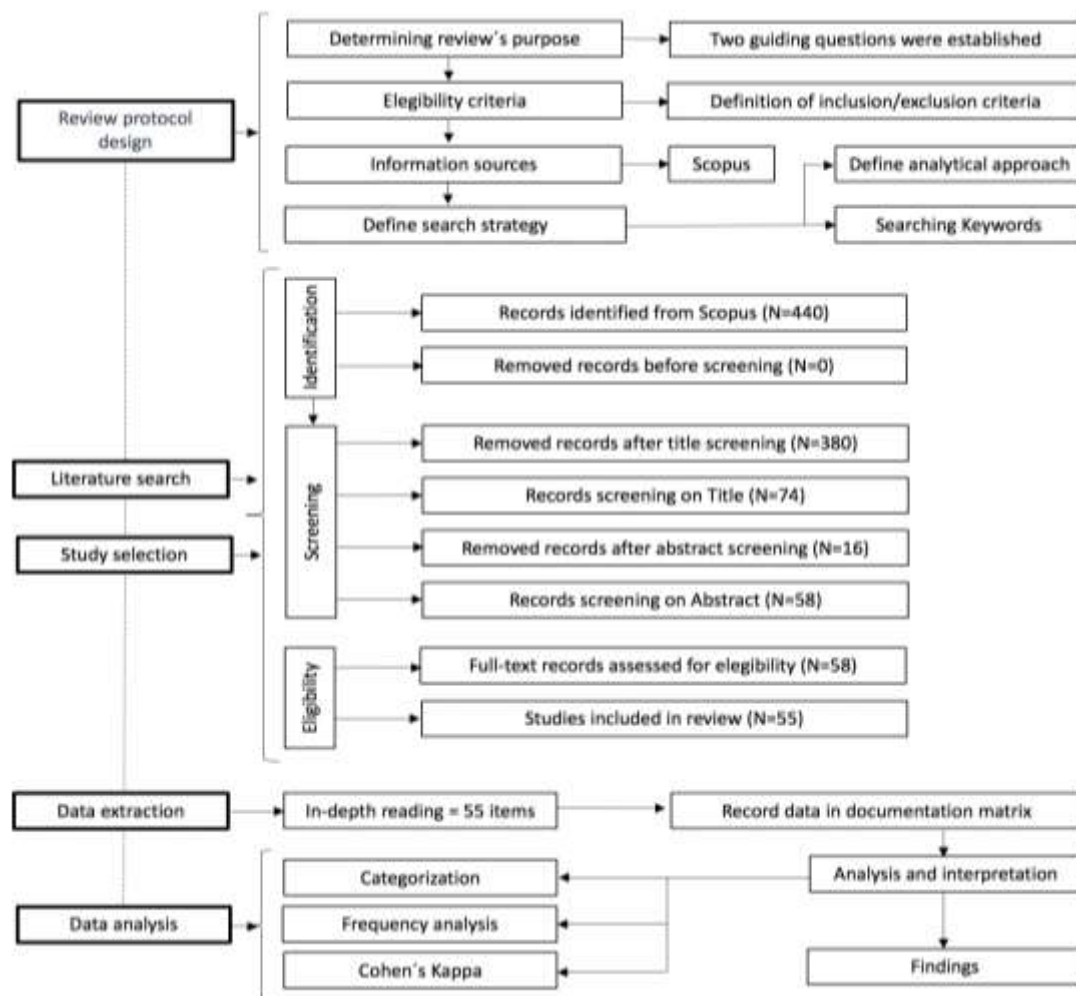


Figure 2. Review process

2.1 Review Protocol Design

2.1.1 Determining the review's purpose.

The primary objective of this review is to examine how learning personalization has evolved over time, with a particular focus on AI-driven methodologies. By synthesizing existing research, this study aims to identify predominant trends, key theoretical approaches, and challenges in implementing AI-based personalization strategies in education. Understanding these aspects will contribute to the development of more effective, equitable, and scalable AI-driven educational frameworks.

2.1.2 Eligibility Criteria

The characteristics of the studies were specified as the basis for making decisions about their selection and inclusion in the review, which are listed in Table 1.

Table 1

Study inclusion and exclusion criteria

Inclusion	Exclusion
1. Articles that present research results	1. Working papers
2. Context: Higher Education	2. Conference proceedings
3. Approach: pedagogical (not technological)	3. Approach to the subject from advanced engineering techniques
4. Presentation of characteristics of personalized learning	4. Contexts other than education
5. Language: English, Spanish and Portuguese	

2.1.3 Information sources

Scopus was used as a source of information since it is a database that includes a large number of peer-reviewed academic sources, which means that the studies published in journals indexed in Scopus have been evaluated and validated by experts in their respective fields (Adriaanse & Rensleigh, 2013). In addition, as stated by Vieira & Gomes (2009), using this particular source is practical for supporting a literature review since it has an advanced search functionality that allows users to perform precise and specific searches and complementary search processes. Filtered with different criteria. Complementarily, Scopus offers a variety of data visualization and analytical tools that help researchers analyze search results and identify trends and patterns in the literature.

2.1.4 Search strategy

As a first step in the definition of the search strategy, a term homologation process was carried out to include various keywords that had the same meaning and thus covered broader and more comparable results. In this way, “Personalized learning” was considered as the base term and two comparable terms were found: “customized” and “individualized”. An initial search turned up a third recurring term called “individual instruction”. Finally, and in keeping with the general purpose of the review, the search context was limited to “higher education” and no particular period was defined to limit the search results.

As a result of this process, the following search string was defined: TITLE-ABS-KEY (“higher education”) AND ALL (“individualized learning” OR "personalized learning" OR "customized learning" OR "individual instruction"), from which 1136 published documents were identified.

2.2 Literature search and Study selection

2.2.1 Identification

From a filtering process by "Higher education", 440 enabled documents were identified for review. By using only Scopus as a source of information, there was no need to eliminate duplicate or repeated items at this stage.

2.2.2 Screening

After applying the inclusion and exclusion criteria, through a screening process, the set of documents was reduced to 380 items. A later process applied to the titles of the documents reduced it again to 74 items. Finally, 16 more documents were eliminated after an abstracting process.

2.2.3 Eligibility

After a preliminary review, it was identified that 3 articles did not provide sufficient information for the analysis, for which they were discarded. From there, a final set of documents was formed to proceed to the in-depth reading of 55 articles.

2.3 Data extraction

This process was carried out using an in-depth reading of the articles that finally passed to the last set of documents. Data related to the two guiding questions of the review were systematically extracted and recorded in a documentation matrix for subsequent analysis. To enhance reliability, data extraction followed a structured protocol to ensure consistency and accuracy. Each selected study was analyzed according to predefined categories, including theoretical framework, methodology, AI-based personalization approach, and reported outcomes. A coding scheme was

developed to classify and synthesize findings, ensuring systematic categorization across diverse studies.

2.4 Data analysis

For the bibliometric analysis, the VOSviewer software was used to find relevant terms and relationships between them that would allow a better understanding of the query results. With the data recorded in the documentation matrix, two complementary analysis processes were carried out. The first involved qualitative grouping and categorization of themes, ensuring an in-depth understanding of key personalization strategies. The second consisted of a quantitative approach based on frequency analysis, which helped identify dominant trends and recurring themes in AI-driven personalization. To reinforce methodological rigour, inter-rater reliability checks were performed, with independent coders verifying consistency in category assignments. A Cohen's Kappa coefficient above 0.812 was considered an acceptable threshold for coding agreement.

2.5 Mitigation of Bias in Study Selection

Addressing potential biases in study selection is crucial to maintaining the integrity of the review. To minimize selection bias, a multi-researcher validation approach was implemented, where independent reviewers conducted parallel screenings of the identified studies. Any discrepancies in selection decisions were resolved through discussion and consensus. Additionally, a secondary validation was conducted using cross-referencing techniques, ensuring that key studies were not inadvertently omitted from the analysis.

Moreover, efforts were made to mitigate publication bias by including studies from diverse regions and institutional contexts, preventing an overrepresentation of research from specific geographical areas. Given the reliance on Scopus as the primary database, potential limitations in coverage were acknowledged, and suggestions for further cross-database comparisons were provided in the discussion.

2.6 Validity and Reliability Considerations

Ensuring the validity and reliability of the data collection and analysis process was a key priority in this review. To enhance validity, triangulation techniques were employed, comparing findings with existing literature reviews and meta-analyses. Additionally, sensitivity analyses were conducted to test the robustness of the results, verifying whether variations in inclusion criteria significantly altered the conclusions.

Reliability was reinforced through the use of standardized protocols for data extraction and coding. Training sessions were conducted for researchers involved in the coding process, ensuring a shared understanding of classification criteria. Furthermore, systematic documentation practices were implemented to enhance transparency and reproducibility in the data analysis process.

Findings

3.1 Results related to the first review question

The review addresses the question: How has the concept of personalized learning evolved over time? Findings reveal that personalized learning has been a core theme in educational discourse for decades, with evolving definitions and varying degrees of complexity and practical application. This conceptual diversity highlights multiple pathways for integrating Artificial Intelligence (AI) into personalized education.

3.1.1 The 1980s and 1990s: Individualized Instruction and Personal Computing

Certainly the personalization of learning has been understood in different ways over the years. The first publications found from the late 70's to the 90's present a marked emphasis on instruction, where attention is drawn to the need to transform teaching methods, whether they are addressed to small groups or directly to the individual. Examples of the above are found in Collier (1985) and (1980) and in Sullivan (1984). A variation of the above directs personalization towards the curriculum, which results in a broader view of the concept since it addresses aspects other than instruction and gives it a more institutionalized characteristic, placing special emphasis on the tension between social changes and needs of individual students (Rose, 1988).

At the end of the 80's and mid-90's, the personalization of learning was associated with digital transformation, due to the process of massification of personal computers and with them the potential to promote self-directed learning, especially making use of the multisensory stimulation generated by multimedia digital content and the interactive web. Examples of the above are found in Hedberg & McNamara (1989), Matthews (1991) and Nobar et al. (1996).

While research from this period emphasized individualized instruction and personal computing as major drivers of learning personalization, many studies overlooked the practical constraints in implementation. The idea that digital tools alone could foster self-directed learning was largely untested at scale, often ignoring socio-economic and accessibility issues. Furthermore, the focus on instructional methods over learner autonomy raises concerns about whether these strategies

genuinely enabled personalization or merely digitized traditional models. Subsequent research needs to re-evaluate these early assumptions, ensuring that personalization strategies genuinely empower learners rather than reinforcing top-down instructional approaches.

3.1.2 The 2000's - 2020's: Hypermedia, learning styles and special educational needs.

The beginning of the millennium marked an accent on the relationship between personalization and learning styles through the implementation of technologies and the development of digital skills, especially through "hypermedia" and other adaptive developments, opening the way for the Consolidation of a key concept of personalization within the framework of 21st-century education: personal learning routes.

In addition, another perspective of the personalization of learning that deserves an independent discussion is highlighted when referring to people with special educational needs, mentioning how the institutionalized system has left this population without opportunities, which of course requires very special characteristics. Examples of the above are found in Vogel & Klassen (2001), Johnson (2006), Wheatly et al. (2010) and Grigoriadou et al. (2010).

Although the literature acknowledges the role of hypermedia and learning styles in learning personalization, several critical issues remain unresolved. One major concern is the lack of empirical support for learning styles as a basis for personalized education. Despite its widespread acceptance, numerous studies have challenged the effectiveness of learning styles in improving educational outcomes. Research suggests that cognitive flexibility, metacognition, and adaptive learning strategies may be more influential in achieving deep learning, yet many AI-based personalization models still rely on outdated learning style classifications. Consequently, AI-driven personalization risks reinforcing superficial categorization, limiting students to predetermined labels rather than fostering diverse cognitive engagement.

Additionally, while hypermedia environments enhance student engagement, their effectiveness varies depending on learner characteristics, digital literacy, and instructional design. Many studies highlight that simply providing hypermedia content does not guarantee improved learning outcomes. In some cases, students struggle with cognitive overload, distraction, and inefficient self-regulation, particularly in open-ended, AI-driven learning environments. Furthermore, AI-based recommendations in hypermedia learning platforms often prioritize engagement metrics over pedagogical depth, leading to passive content consumption rather than active knowledge construction. Future research must address how AI can facilitate more meaningful interactions

within hypermedia environments, ensuring that learning personalization fosters critical thinking rather than mere content exposure.

Regarding special educational needs (SEN), while AI-powered personalization promises greater inclusivity, practical implementation remains uneven. Many AI-driven tools lack adaptability for students with cognitive, sensory, or motor impairments, often focusing on general learning enhancements rather than specific accessibility needs. Moreover, personalization in SEN remains highly dependent on resource availability, institutional support, and teacher training. Without equitable infrastructure, AI may widen rather than bridge the accessibility gap, reinforcing existing educational disparities. To ensure ethical and effective AI-driven personalization, future studies must investigate the intersection of AI, hypermedia, and inclusive education, ensuring that AI-based learning environments adapt to diverse learner needs while avoiding over-reliance on outdated pedagogical assumptions.

3.1.3 The 2010s to present: Mobile and intelligent technologies

The latest phase of personalized learning research emphasizes the development of intelligent environments as a key approach to creating learning experiences tailored to individual objectives and interests. In this context, the semantic web, adaptive and mobile e-learning, self-organized learning environments (SOLEs), hybrid models, gamification, and Personal Learning Environments (PLEs) have emerged as essential mediators of personalization in contemporary education. These frameworks enable students to engage with dynamic, interactive, and student-centered learning experiences, leveraging technology to adapt educational content to diverse learning needs (de Freitas et al., 2015; Hyndman et al., 2011; Keppell, 2014; Marín Juarros et al., 2014; Murray & Pérez, 2015; Oussena et al., 2011; Taylor, 2014).

Simultaneously, technologies associated with the Fourth Industrial Revolution—including Big Data, learning analytics, and artificial intelligence (AI)—are playing an increasingly dominant role in shaping personalized learning. By harnessing large-scale data analysis, these technologies promise to move education beyond traditional, standardized models, offering adaptive, real-time learning experiences. AI-powered personalization analyzes student data, predicts learning needs, and dynamically adjusts content, making learning pathways more flexible and responsive (Alameen & Dhupia, 2019a; Altaie & Norhayati. Abang Jawawi, 2021a; Christodoulou & Angeli, 2022a; Dziuban, Howlin, Moskal, Johnson, Eid, et al., 2018; Oussena et al., 2011; Scott & Nichols, 2017a);

However, despite these advancements, significant challenges remain. AI-driven personalization heavily depends on vast datasets, yet many educational institutions lack the infrastructure to collect and process such data ethically and efficiently. Moreover, while AI is often presented as an objective and neutral tool, existing research tends to overlook algorithmic biases embedded in training data. If unaddressed, these biases risk reinforcing educational inequalities rather than mitigating them.

Future research must critically evaluate the real-world impact of AI-driven personalization, ensuring that adaptive technologies benefit diverse learner populations rather than creating rigid, pre-defined learning trajectories. A balanced approach—one that integrates AI with human oversight, safeguards data privacy, and prioritizes inclusivity—is essential to ensuring equitable and ethical advancements in personalized learning.

3.2 Results related to the second review question

The review explores methods and techniques used in learning personalization, highlighting two main approaches: teacher-led personalization and student-centred personalization. The former focuses on instructional strategies, while the latter emphasizes individual learning needs.

3.2.1 Teacher-Led Personalization

Brass and Lynch (2020) suggest that all learning is inherently personalized, as each learner constructs knowledge differently. However, traditional teaching models have struggled to meet diverse learning needs (Benegas & Sirur Flores, 2019). Despite its pedagogical relevance, teacher-led personalization faces scalability challenges. Programmed learning, individualized profiles, and tutoring demand significant human effort, making large-scale implementation difficult without AI mediation. Moreover, few studies compare teacher-led and AI-driven personalization, leaving gaps in understanding which aspects of human-led teaching are indispensable. Further research should evaluate how AI can support, rather than replace, teacher-led personalization, ensuring that technology enhances rather than dominates instructional processes.

3.2.1.1 Programmed Learning, Learning Profiles, and Tutoring

Historically, programmed learning was used to structure content sequentially, allowing students to progress from basic to advanced concepts (Sadykov et al., 2023). However, despite its intent to provide adaptive learning, it often lacked flexibility, offering predefined responses rather than truly personalized feedback (Fariani et al., 2023). Additionally, its standardized approach failed to accommodate diverse learning styles, limiting its effectiveness in fostering deep learning. Another

approach involved individualized learning profiles, which aimed to identify student strengths, abilities, and preferences to tailor instruction (Klašnja-Milićević et al., 2020). Despite its potential, developing these profiles required extensive data collection, making it logistically challenging and resource-intensive (Regan & Jesse, 2019).

Finally, personalized tutoring was explored as a means of adapting instruction to individual student needs. The effectiveness of tutoring depended largely on the relationship between tutor and student, which fostered trust and engagement (McIntosh & Ferguson, 2017). However, scaling personalized tutoring remained impractical due to high student-teacher ratios, making one-on-one instruction difficult to implement at larger levels (Kozierkiewicz-Hetmańska, 2012).

Ultimately, while teacher-led personalization has demonstrated educational benefits, scalability, resource constraints, and methodological rigidity have limited its widespread adoption. AI integration presents opportunities to enhance these strategies, but its role must be critically examined to ensure it complements rather than replaces traditional teaching methods.

What could be the contribution of artificial intelligence concerning the above?

Existing research presents AI as an enhancer of programmed learning, individualized profiles, and tutoring, yet many studies fail to account for learner agency. While AI excels at automating pattern detection, it may narrow learning pathways rather than expand them, particularly when systems prioritize efficiency over exploration. Additionally, AI-driven learning profiles raise concerns about data privacy and ethical profiling, as misinterpretations of student data could lead to rigid categorizations that restrict opportunities rather than enabling flexibility. A more nuanced perspective is needed, ensuring that AI complements rather than dictates personalized learning trajectories.

Given the technological limitations of the time, most of the difficulties in achieving personalization of learning using existing strategies proved difficult to overcome. However, in the current technological context, driven by artificial intelligence, it is possible to train systems to provide immediate and personalized feedback based on data about students' styles, preferences and interests, collected through their interaction in information networks. These trained systems can adapt individualized content, activities, and feedback in response to students' online activities.

3.2.1.2 Sequence Analysis and Corrective Instruction

Sequence analysis examines how students interact with learning activities, identifying trends, strategies, and difficulties in their learning process (Ji et al., 2018). This approach provides insights

into where students struggle and how to offer targeted support. Similarly, Corrective Instruction aims to detect problem areas and deliver personalized interventions to address learning gaps.

Both strategies rely heavily on assessment data to track individual student progress (Villatoro Moral & de-Benito Crosseti, 2022). However, in large-scale educational settings, teachers face challenges in collecting, analyzing, and acting on student data efficiently. Moreover, adapting activities and providing real-time personalized support remains difficult, particularly in classrooms with diverse learning needs.

How to overcome these obstacles using AI?

AI can enhance sequence analysis and corrective instruction by enabling scalable and efficient data processing. Automated systems can quickly identify common error patterns and individual student needs, reducing the time and effort required by educators. Additionally, AI facilitates continuous monitoring, offering real-time feedback that would be impractical for human instructors to provide consistently.

However, AI-based learning analytics are not without risks. While they can identify learning gaps, research on algorithmic fairness suggests that AI-driven feedback may reinforce biases, particularly if training data lacks diversity. Additionally, constant AI-generated corrections may lead students to over-rely on automated guidance, potentially hindering critical thinking and self-regulated learning.

Future research should assess AI's pedagogical and psychological effects, ensuring that AI-driven personalization enhances learner autonomy rather than fostering dependency. When implemented responsibly, AI can optimize sequence analysis and corrective instruction, making personalized learning more scalable, accurate, and time-efficient for educators.

3.2.1.3. Adaptation of assistive methods and technologies.

Adaptation in education involves differentiated teaching approaches that address the abilities and limitations of students with disabilities. This includes multisensory strategies, adapted materials, visual and tactile supports, positive reinforcement, and continuous feedback (Benmarrakchi et al., 2019; Sharef et al., 2021). These methods aim to provide meaningful and accessible learning experiences, equipping students with the tools to overcome educational barriers.

Assistive technologies complement these efforts by integrating specialized tools designed to support learners with disabilities. These include screen readers for the visually impaired, adapted keyboards for motor disabilities, voice recognition software, and real-time translation tools (Azizi

et al., 2022; Marienko et al., 2020). Such technologies enable greater autonomy and active participation in learning environments.

However, implementing assistive methods and technologies requires careful planning, individualized approaches, and collaboration between educators, inclusion specialists, and therapists. The high costs of these adaptations pose challenges for educational institutions and families, limiting accessibility. Additionally, many educators lack the training to effectively implement assistive technologies, further reducing their impact (Flanagan et al., 2013).

How could these obstacles be addressed using AI?

AI can enhance accessibility by creating personalized learning resources tailored to individual needs. Using machine learning and natural language processing, AI can analyze student profiles and recommend appropriate resources and adaptations (Rodriguez-Medina et al., 2022; Salinas Ibáñez et al., 2022). Moreover, AI-driven real-time support systems—such as intelligent screen readers, sign language translators, and speech-to-text recognition—can facilitate content access and improve student engagement (König et al., 2022). Despite its potential, AI-enhanced assistive tools remain costly and are primarily available in well-funded institutions. Without equitable access and proper teacher training, these technologies risk widening the educational divide rather than reducing it. Future research should assess not only AI's effectiveness but also its feasibility in diverse educational contexts, ensuring inclusive and scalable solutions.

3.2.2 Student-driven personalization.

Historically, most research on learning personalization has focused on teacher-led approaches, where educators analyze student data to adjust learning resources and activities (Alamri et al., 2020; Liu et al., 2022; Mesquita et al., 2017). While this exogenous perspective is valuable, a student-centred approach—where learners actively co-create their educational pathways—is gaining relevance in 21st-century education (Alamri et al., 2020; Villatoro Moral & de-Benito Crosseti, 2022). Thus, student-driven personalization prioritizes learner autonomy, allowing students to make informed decisions about their learning process (Fiedler & Våljetaga, 2020; Gillaspay & Vasilica, 2021; Sharef et al., 2021).

In this regard, Technologies such as mobile learning (Bai, 2019), IoT (Xie & Yang, 2021), and Smart Learning Environments (Agbo et al., 2019), facilitate this autonomy, enabling students to customize their learning experiences using Personal Learning Environments (PLEs) and

personalized dashboards. These tools empower students to visualize progress and take control of their education.

Furthermore, AI-driven personalization offers real-time adaptability, dynamically adjusting learning pathways based on student interactions (Cavanagh et al., 2020; Grigoriadou et al., 2010; Liu et al., 2022). In this regard, Systems built on natural language processing are advancing toward smart tutoring technologies, providing tailored support and adaptive materials (Rof et al., 2022; Zhang et al., 2022).

However, despite these benefits, AI-driven student personalization presents challenges. Many studies assume AI-generated pathways inherently align with learner needs, yet over-standardization risks limiting exploration. AI may guide students into predefined trajectories, restricting diverse learning opportunities. Additionally, research rarely considers student perceptions of algorithmic decision-making, particularly when AI recommendations conflict with individual learning preferences. A critical gap remains in understanding how students engage with AI-driven personalization. Future research must ensure that AI enhances autonomy rather than dictating learning pathways, preserving student agency, flexibility, and critical decision-making.

Discussion, Conclusion and Implications

In an increasingly globalized and technologically advanced society, learning personalization has emerged as a key pedagogical approach, addressing students' individual needs, strengths, and learning styles (Gowda & Suma, 2017). Moving beyond traditional, uniform education models, personalized learning integrates teacher-led and student-driven strategies, adapting to societal demands and diverse learner profiles.

Over the past four decades, personalized learning has evolved from individualized instruction to AI-driven approaches. The most effective models incorporate adaptive techniques that allow students to make decisions about their learning pathways (Su et al., 2011). This shift represents a move away from teacher-centred instruction, promoting learner autonomy and dynamic educational experiences.

Despite its potential, scaling AI-driven personalized learning presents challenges. Data privacy and ethical concerns remain pressing, as AI relies on extensive data collection, raising questions about student consent, data security, and algorithmic bias. Many institutions lack clear AI governance policies, leading to opaque decision-making and potential misuse of student data.

Additionally, the digital divide creates disparities in AI adoption. While well-funded institutions implement advanced AI-driven personalization, under-resourced schools struggle with outdated technology and limited digital literacy. Without targeted policies to bridge this gap, AI may exacerbate rather than reduce educational inequalities.

Another obstacle is institutional resistance to AI adoption. Many educators lack adequate training, leading to scepticism about AI's pedagogical value. Furthermore, financial and infrastructural limitations hinder large-scale implementation, requiring investment in teacher development, IT infrastructure, and AI policies. Ensuring faculty training is crucial so that AI serves as a complementary tool rather than replacing human instruction.

To implement effective personalized learning, education must integrate traditional and AI-enhanced methods, adapting to evolving student needs. A student-centered approach is essential, empowering learners to actively participate in their education. However, responsible AI implementation must prevent over-automation, bias reinforcement, and ethical misuse of data, ensuring equitable and sustainable learning personalization.

4.1 Practical Implications for Higher Education Institutions

To ensure the effective and ethical implementation of AI-driven personalized learning, a multi-level approach must be considered, addressing educators, institutional decision-makers, and policymakers.

4.1.1 For Educators: AI as a Support for Differentiated Instruction

AI offers powerful tools to enhance differentiated instruction, allowing educators to tailor content, adapt assessments, and provide individualized feedback at scale. AI-driven learning analytics can assist teachers in identifying students' strengths and weaknesses, offering real-time intervention strategies. However, teacher training is critical to ensuring that AI remains an instructional aid rather than a determinant of learning pathways. Educators must be equipped with critical digital literacy skills to interpret AI-generated recommendations while maintaining professional autonomy in pedagogical decision-making.

4.1.2 For Institutions: AI Adoption Strategies

The integration of AI in higher education requires institutional readiness, including robust IT infrastructure, data governance policies, and ongoing professional development programs. Universities must establish clear ethical guidelines for AI implementation, ensuring that personalization efforts do not compromise student privacy or academic integrity. Additionally,

institutions should develop multi-stakeholder collaboration models, involving educators, technologists, and students in AI design and implementation. Funding allocation should prioritize inclusive AI strategies, ensuring that personalization technologies are accessible across diverse socio-economic contexts rather than being confined to elite institutions.

4.1.3 For Policymakers: Ethical and Regulatory Considerations

Policy frameworks must evolve to address the ethical challenges associated with AI-driven personalization. Regulatory measures should establish clear boundaries on student data collection, algorithmic transparency, and AI accountability. Governments and accreditation bodies should enforce standards for ethical AI usage in education, ensuring that personalization technologies align with principles of fairness, non-discrimination, and academic integrity. Furthermore, public policies must include funding mechanisms that support infrastructure development and digital inclusion, preventing AI-driven learning personalization from deepening existing educational inequalities.

By addressing these practical and ethical considerations, the integration of AI in personalized learning can move beyond technological optimism, ensuring that its implementation is both effective and equitable within higher education institutions. Future research should focus on longitudinal studies that examine the real-world impact of AI on learning outcomes, offering evidence-based insights that guide responsible AI adoption in education.

4.2 Future Research Directions

While this study provides a comprehensive examination of AI-driven learning personalization, several areas warrant further investigation. Future research should explore longitudinal studies that assess the sustained impact of AI on learning outcomes, moving beyond short-term engagement metrics. Additionally, comparative studies between AI-based and teacher-led personalization models would offer deeper insights into their respective effectiveness and limitations.

Further inquiries should also address the psychological and cognitive effects of AI-driven personalization, particularly regarding student autonomy and decision-making. As AI systems become more embedded in education, understanding their influence on learner agency, motivation, and cognitive development will be crucial.

Finally, future research must consider the ethical dimensions of AI implementation, including algorithmic bias, data privacy, and inclusivity. Examining policy frameworks and institutional best

practices for mitigating these risks will be essential in shaping AI-driven education that is both innovative and equitable.

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