

Review

Key Barriers to Personalized Learning in Times of Artificial Intelligence: A Literature Review

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Abstract: Personalized learning (PL) has emerged as a promising approach to address diverse educational needs, with artificial intelligence (AI) playing an increasingly pivotal role in its implementation. This systematic literature review examines the landscape of PL across various educational contexts, focusing on the use of AI and associated challenges. Using the PRISMA guidelines, 68 empirical studies published between 2018 and 2024 were analyzed, revealing correlations between academic levels, learning modalities, technologies, and implementation barriers. Key findings include (a) predominant use of AI in higher education PL implementations, (b) preference for blended learning in secondary and elementary education, (c) shift from technological to pedagogical barriers across educational levels, and (d) persistent psychological barriers across all contexts. This review provides valuable insights for educators, policymakers, and researchers, offering a comprehensive understanding of the current state and future directions of AI-driven personalized learning.

Keywords: personalized learning; artificial intelligence; education 4.0; systematic review; adaptive learning; educational technology; higher education; educational innovation



Academic Editor: Douglas
O'Shaughnessy

Received: 8 February 2025

Revised: 21 February 2025

Accepted: 25 February 2025

Published: 13 March 2025

Citation: Barrera Castro, G.P.; Chiappe, A.; Ramírez-Montoya, M.S.; Alcántar Nieblas, C. Key Barriers to Personalized Learning in Times of Artificial Intelligence: A Literature Review. *Appl. Sci.* **2025**, *15*, 3103. <https://doi.org/10.3390/app15063103>

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1. Introduction

In the context of the Fourth Industrial Revolution, the personalization of learning has become crucial, as it represents the increasing integration of human capabilities with technological advancements [1]. This phenomenon is driven by disruptive technologies such as artificial intelligence (AI), the Internet of Things, and robotics. AI, defined as the ability of machines to process data through algorithms, learn from patterns, and apply that knowledge in decision-making similarly to humans [2], has made significant advancements. From the first intelligent tutoring systems to personalized learning environments [3], AI has facilitated the provision of resources and assessments tailored to each student, adapting to their profile, learning style, and cognitive levels [4,5]. Moreover, biometric and contextual tracking technologies have emerged, enabling the detection of emotions and preferences, thus allowing systems to be adjusted more precisely to students' needs [6].

Consequently, the development of AI represents a transformative opportunity for educational ecologies and traditional learning processes. In this regard, humans have diverse educational goals, learning styles, and individual characteristics that influence their formation. Therefore, personalized learning (PL), understood as student-centered education, is seen as an alternative capable of addressing these differences through the use of technology, thus contributing to improving the quality of education [7]. In this context, PL allows instruction to be tailored to students' preferences, needs, and learning paces [8]

through mechanisms such as Learning Analytics, which identifies individual characteristics and adjusts learning materials, spaces, and contexts accordingly [9].

According to the OEI-UNESCO [7], understanding the diverse nature of PL is essential for advancing its implementation. In this regard, it is important to take into account their prior knowledge, needs, and abilities [10]. In the same way, Lee et al. [11], indicate that PL adapts instructions by considering differentiation, individualization, and inclusion.

However, despite the widely documented advantages of PL, significant challenges persist, particularly in an educational context increasingly influenced by disruptive technologies such as AI. In this context, this literature review seeks to identify and analyze barriers that have been historically reported in the implementation of PL environments and may still be relevant today. Although PL has been the subject of extensive discussion, the literature identifies several obstacles that have yet to be overcome. These barriers can be classified into five dimensions: (1) Conceptual Barriers, which refer to the diversity in the understanding and implementation of concepts related to PL [12–15]; (2) Institutional Barriers, which include resistance to change, lack of technological infrastructure, insufficient time, inadequate institutional support, and funding difficulties [8,16–18]; (3) Psychological Barriers, related to the perception of additional workload, distrust in technological skills, and lack of motivation towards PL [19,20]; (4) Technological Barriers, which include limited access to technology, deficiencies in digital skills, insufficient technical support, integration difficulties, and ethical considerations [16,21–24]; and (5) Pedagogical Barriers, related to the models used for personalized instruction, the lack of pedagogical knowledge necessary to adapt content and learning activities, insufficient pedagogical support for teachers, and the complexity of measuring and tracking students' individual progress [25–28].

In this regard, it is worth mentioning that to date no clear categorization of these barriers has been found through a review of empirical studies on PL. Thus, this literature review seeks to fill that gap, identifying areas of opportunity and technological trends. In this way, the objective is to provide value to both academic communities and policymakers interested in effectively implementing PL as an alternative to reduce gaps in the quality of education.

Indeed, the concept of PL has been discussed by theorists and educators over time, who have emphasized its importance for achieving equity, effectiveness, and inclusion in education. For example, among the most prominent developments are the proposals of Maria Montessori, with her method of individualized learning and holistic development [29], Bloom's Taxonomy, which classifies educational objectives at different levels and proposes adaptive instructions [30], and Vygotsky's Theory of Cognitive Development, which conceptualizes the gap between a learner's current level of development and their potential future development, achievable through an appropriate collaborative learning environment [31]. Despite the significant contributions of these authors, the challenge of achieving effective PL persists today.

Likewise, the use of emerging and current technologies plays a fundamental role in achieving effective PL. For example, the educational implementation of software and algorithms allows for the personalization of content, assessment, teaching strategies, and curricular options for both students and teachers [32]. Moreover, Generative AI with a human likeness with social behavior capabilities are beginning to complement the work of teachers, especially in assisting with practical tasks and improving the mastery of prior knowledge [33]. In this context, AI stands out as a transformative catalyst that offers unprecedented capabilities for student profiling, adaptive content delivery, and real-time feedback [1]. In this context, Personalized Learning leverages AI and data analytics to tailor education, but it also raises concerns about surveillance capitalism. Institutions and corporations collect vast amounts of student data, including cognitive patterns and personal

behaviors, which can be exploited for commercial interests. This extensive data tracking risks turning students into products rather than beneficiaries of learning innovations. Additionally, AI-driven decision-making may introduce biases, reinforcing educational inequalities instead of reducing them. To prevent misuse, strong regulatory frameworks are necessary to ensure transparency, restrict data retention, and prohibit commercialization. Educational institutions must implement ethical AI practices, limiting data collection to essential learning improvements while protecting student privacy. Moreover, students and educators should have control over how their data is used, fostering an environment where technology enhances education without compromising individual rights. Personalized learning should empower learners, not subject them to hidden surveillance and corporate exploitation.

Lastly, the significant changes that characterize the contemporary world demand more relevant education, capable of preparing students to face the demands of the 21st century. In this sense, Fourth Industrial Revolution technologies, such as AI, the Internet of Things, robotics, extended realities, cybersecurity, and cloud computing [34], have become essential components of face-to-face, hybrid, and distance learning. For this reason, future professionals must integrate these emerging technologies into their practices to achieve higher levels of competitiveness and efficiency [9].

2. Method

This systematic literature review (SLR) was conducted following the principles of the PRISMA statement [35] and the methodology outlined by Kitchenham et al. [36] and Linnenluecke et al. [37], which facilitate a structured examination of the phenomenon by systematically collecting, evaluating, and summarizing research findings. This approach facilitates access to and understanding of the evidence, ensuring rigor through five main phases: (1) the formulation of research questions, (2) the design of a search protocol, (3) the definition of inclusion and exclusion criteria, (4) the execution of a selection and data extraction process, and finally, (5) a data synthesis process, as shown in Figure 1.

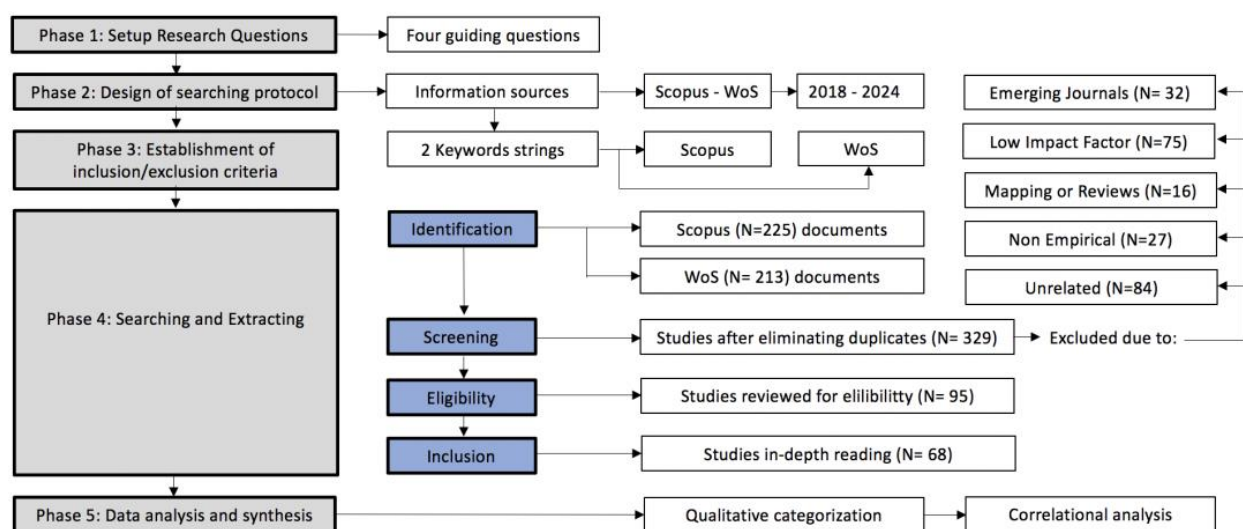


Figure 1. Phases of the Systematic Literature Review Process.

2.1. Formulation of Research Questions

To analyze personalized learning experiences revealed by the literature through empirical research findings, the researchers formulated four questions, following the SMART method criteria for the formulation of research questions [38], which are presented below:

RQ1. What research methods are predominantly used in studies published between 2018 and 2024, and how do they contribute to the outcomes of personalized learning?

RQ2. Which technologies are most frequently utilized in studies published between 2018 and 2024 to achieve personalized learning, and how are they applied across different educational contexts?

RQ3. What instructional modalities (e.g., online, blended, face-to-face) are most commonly reported in studies focused on personalized learning between 2018 and 2024, and what patterns or trends can be identified?

RQ4. What barriers to the implementation of personalized learning are reported in studies published between 2018 and 2024, and how do these barriers vary across different educational levels or regions?

2.2. Search Protocol

The article search was conducted using the Scopus and Web of Science (WoS) databases, which are widely recognized for their rigorous content selection and broad disciplinary coverage. According to Airyalat et al. [39] and Pech and Delgado [40], these databases ensure the reliability of sources and provide advanced filtering and analysis tools that are particularly beneficial for literature reviews. The defined search parameters included the following keywords: personalized learning, adaptive learning, personalized adaptive learning, experience, and case study. The search was limited to articles published between 2018 and 2024, written in English, and categorized as peer-reviewed journal articles. The resulting search strings are detailed in Table 1.

Table 1. Search strings used in the databases.

Scopus	Web of Science (Wos)
TITLE-ABS-KEY ("personalized learning" OR "personalized adaptative learning" OR "adaptative learning" AND experience OR case AND study) AND PUBYEAR > 2017 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English"))	((("personalized learning" OR "personalized adaptative learning" OR "adaptative learning") AND (experience OR case AND study)) (All Fields) and 2024 or 2023 or 2022 or 2021 or 2020 or 2019 or 2018 (Publication Years) and Article (Document Types) and English (Languages)

2.3. Inclusion and Exclusion Criteria

Factors limiting personalized learning were addressed based on the challenges reported in studies implementing this approach with empirical research results. The inclusion criteria included the aforementioned time period and language, as well as empirical articles with research findings and those containing the defined search terms in their title, abstract, or keywords. Exclusion criteria included other types of publications, such as literature reviews, book chapters, books, reviews, and publications in emerging journals or articles published before the defined time frame.

2.4. Selection and Data Extraction Process

A total of 438 articles were retrieved from the Scopus and WoS databases. After removing 109 duplicate studies and 32 publications from emerging journals, quality criteria were applied to ensure the selection of high-impact, empirical research that explicitly addressed personalized learning in their titles, abstracts, or keywords. This process led to the exclusion of an additional 202 studies. Subsequently, the remaining articles were carefully reviewed to identify those reporting challenges in implementing personalized learning. This review resulted in the elimination of 27 more articles that either did not address difficulties in PL implementation or were not directly related to the topic. Ultimately, 68 articles (48 from Scopus and 20 from WoS) were selected, and the following data were extracted: authors,

keywords, title, year, journal, impact quartile, number of citations, DOI, language, country, and abstract.

2.5. Data Analysis and Synthesis

To support the content analysis of the articles based on the research questions, a data extraction matrix was used, which can be consulted online. The qualitative analysis technique used was referenced by Vindrola-Padros & Johnson [41] and Mayring [42], where objective inferences were made from the extracted data on emerging categories of analysis to address the review questions.

Also, a Spearman correlational analysis was conducted on a dataset comprising 68 studies on personalized learning across various educational levels. A quantitative approach was employed to examine the relationships between four key variables: academic level, learning modality, technology used, and barriers encountered. Frequency counts and percentages were calculated for each variable category, and cross-tabulations were then performed to identify correlations between these variables, focusing on the top three occurrences in each category by academic level and modality. The analysis particularly emphasized the relationships between academic levels (Higher, Secondary, Elementary, and Continuous) and other variables. Percentages were calculated relative to the total number of studies within each academic level to facilitate comparisons. This method allowed the identification of distinct patterns and trends in PL implementation across different educational contexts, revealing how approaches to PL vary according to academic level and the challenges specific to each context.

3. Results

This section presents the findings related to the research questions. These include some general characteristics of studies on PL, the technologies used to facilitate PL, and the factors that may hinder its implementation.

3.1. General Characteristics of Studies on PL

A networking mapping tool was used to generate a group of clusters regarding the most frequent words related to Personalized Learning presented in the reviewed publications, as illustrated in Figure 2. The creation of Figure 2 involved a systematic process of data extraction, preprocessing, and visualization to highlight key terms related to personalized learning. Initially, textual data were collected from the studies analyzed, focusing on keywords, abstracts, and recurring concepts. Through preprocessing, common words were removed, and terms were standardized to ensure consistency. A frequency analysis was then conducted to identify the most prevalent terms, with prominence given to those appearing most frequently across the dataset. Using visualization tools, a word cloud was generated, where the size of each word corresponded to its relative occurrence. The final figure visually represents dominant themes in personalized learning, facilitating the identification of core research areas.

The three most frequent terms in the dataset are ‘personalized learning’ (56%), ‘personalization’ (18%), and ‘E-learning’ (16%). Other terms appear with lower frequency, reflecting researchers’ diverse strategies for integrating different dimensions into personalized learning. For example, assessment practices such as formative assessment (8%) [43–45], learning environments such as intelligent tutoring systems (8%) [46–48], infrastructures supported by learning analytics (10%) [49,50], resources like game-based learning (8%) [51,52], and augmented reality (2%) [53], among others.



Figure 2. Word Cloud of Key Terms.

3.2. Methodological Strategies in PL Studies

The analysis of publications on PL does not show a clear preference for any of the three research approaches. The trend shows a slight inclination towards mixed methods ($n = 26$ and $f = 38.2\%$), followed by quantitative ($n = 22$ and $f = 32.4\%$) and qualitative methods ($n = 20$ and $f = 29.4\%$).

Mixed methods combine elements of both qualitative and quantitative research, allowing for a more comprehensive and nuanced understanding of the phenomenon under study. This approach can be particularly useful when quantitative data alone is insufficient to understand the full context of a problem [54]. For example, Almousa & Alghowinem [55] conducted a study in which they designed an autonomous robot tutor that delivers personalized lesson content and interacts with preschool children. Their research focused on the effectiveness of the social robot for learning, including different factors such as behavior, the unique characteristics of children when interacting with machines, and the learning impact.

On the other hand, quantitative methods, such as experimental and quasi-experimental designs, are useful for evaluating strategies to achieve PL by comparing experimental and control groups, facilitating the collection of numerical data and the demonstration of causal relationships [54]. An example is the study by Taherisadr et al. [53], which treated human learning as a sensory input signal and tested their ERUDITE platform, which provided personalized feedback to enhance the educational experience. Evaluating 15 participants, they demonstrated that by using brain signals to adapt to the learning environment, academic performance increased by an average of 26%.

Finally, qualitative methods focus on understanding the meaning and interpretation of social phenomena from the participants' perspective. These methods are useful for exploring complex and contextual phenomena and for developing theories or hypotheses [54]. An example is the study by Pflaumer et al. [56], which sought to understand how teachers adopt NAVIGO technology, an adaptive personalized literacy game used regularly in primary school classrooms.

3.3. Technologies Used in PL Studies

As shown in Table 2, the use of combined technologies to achieve PL stands out (42.6%). These include artificial intelligence (AI), other platforms (OP), learning management systems (LMS), robotics (Rob), extended realities (ER), cloud computing (CC), and social networks (SN). One example is Albano & Dello Iacono (2019) [57], who integrated Moodle with GeoGebra Interactive Formative Test (GIFT), using AI to track and assess students, providing personalized feedback and guidance.

Table 2. Technologies Used to Achieve PL by Number of Studies.

Technology	N° of Studies
Combined technologies	29 (42.6%)
Artificial Intelligence	20 (29.4%)
Other Platforms	12 (17.6%)
Learning Management System	5 (7.3%)
Learning Analytics	2 (3.1%)
Total	68 (100%)

Learning Management Systems (LMS) have evolved beyond their basic functions. Arsovic & Stefanovic's [58] study demonstrated how AI techniques enhance LMS personalization by adapting learning processes based on students' performance and needs. AI, used in 29.4% of studies, improves predictive accuracy, reduces data overfitting [59], and enables personalized scheduling and assessment of reading progress [43].

Additionally, other platforms (OP) contributing to PL are identified, accounting for 17.6%. Examples include the programmatic system of the iREAD project [60] and the pedagogical technological knowledge development environment aimed at teachers [61]. Other technologies, such as LMS and traditional data analysis techniques (LA), also contribute to the process, though to a lesser extent.

3.4. Educational Modalities Related to PL

This study analyzed learning modalities to examine their role in implementing personalized learning (PL). E-learning was the most common approach ($n = 36$, $f = 52.9\%$), followed by blended learning (B-learning) ($n = 24$, $f = 35.3\%$), which effectively integrates virtual and physical environments.

To a lesser extent, face-to-face learning ($n = 4$, $f = 5.9\%$) was identified, which fosters direct and personal interaction in the educational process. Additionally, tools used in both B-learning and E-learning environments were analyzed ($n = 2$, $f = 2.9\%$). Learning through mobile devices, or M-learning ($n = 1$, $f = 1.5\%$), was identified, as well as a study that did not necessarily specify a learning modality ($n = 1$, $f = 1.5\%$), which may indicate the possibility of a more flexible approach to these educational processes.

3.5. Factors Limiting PL

Studies in the systematic review reveal factors that hinder PL at the conceptual, institutional, psychological, technological, and pedagogical levels, as shown in Table 3. It is worth mentioning that multiple categories or subcategories may be mentioned within a single study.

Technological barriers stand out as the greatest challenge, facing obstacles in effectiveness such as adapting content to children's abilities [55], updating conceptual states for some students with significant behavioral differences [62], capturing hidden information

from students that affects their learning experience [63], and the quality of data collection impacting the recommendation of learning paths [64].

Table 3. Categories and subcategories of barriers identified by the number of studies.

Category	# Studies	Subcategories
Conceptual	4 (6.1%)	Implementation Terminology Theoretical
Institutional	10 (14.7%)	Infrastructure Time Workload Financing Teacher training
Psychological	20 (29.4%)	Resistance Emotional Distraction Commitment Motivation
Technological	48 (70.6%)	Design Skills Support Incompatibility Methodology Effectiveness Ethical Access
Pedagogical	29 (42.6%)	Resource Design Evaluation Support Planning Effectively Methodology

Several challenges exist in designing PL environments and enhancing teachers' digital skills. These include difficulties in interpreting neural network results [65], understanding the relationship between motivational factors and E-learning effectiveness [66], and addressing AI limitations, such as GPT-4's restricted numerical reasoning in mathematics feedback [67]. Additionally, expert guidance is often required to manage these environments effectively [50,68,69]. Key areas for improvement include instructional design, digital proficiency, and pedagogical effectiveness in PL processes. To a lesser extent, additional barriers were identified related to support, incompatibility, methodology, ethics, and access.

Pedagogical barriers, the second most frequent category identified, include challenges related to resource design. These challenges involve the continuous calibration of content, tests, and learning objects [70], the development of resources that not only transmit knowledge but also foster skill development [71], and difficulties in content comprehension, particularly for students who are not native speakers [72].

Challenges in effectiveness and pedagogical support were also evident. For instance, variables such as itinerary, the assimilation of methodological strategies, and student organization must be addressed to improve outcomes [73]. The integration of M-learning requires a thorough evaluation of existing teaching and learning methods, as well as content design [74]. There is also a need to complement technical aspects with real pedagogical

scaffolding, including support and guidance to help students learn effectively [44,60]. PL is impacted by limitations in resource management, the effectiveness of methodologies to strengthen skills, and the necessary support to overcome challenges. Additionally, though rarely, obstacles related to evaluation, planning, and design were identified. These aspects directly affect the complexity and optimization of pedagogical processes.

Psychological barriers, the third most frequent category, mainly address the lack of consistent student engagement and participation [44,49,59]. Additionally, resistance from teachers to implement PL was observed, often due to fears of adopting new teaching methods [56] and difficulty recognizing the potential of the tools [75]. Emotional aspects are significant challenges in this category; factors such as stress and anxiety must be considered when designing activities, learning techniques, and teaching methods while maintaining impartiality and fairness [76–78]. The need to address student engagement, overcome teacher resistance, and carefully consider emotional aspects during PL implementation is highlighted. Furthermore, less frequently, barriers related to student motivation and distraction were identified.

Regarding institutional barriers, this is an understudied category, with emphasis on the subcategories of infrastructure and time. The need for adequate electronic devices for students, especially in schools in less developed areas, is highlighted [56,79]. The implementation of a technology-based personalization approach posed challenges, including new responsibilities in the institutional context [80]. Additionally, there is a need for increased funding and efficient organization of teachers' planning time [81].

Concerning conceptual barriers, although they are rarely explicitly addressed, difficulties were identified such as the lack of implementation parameters [82,83], lack of unity in terminology [80], and the diversity of theoretical dimensions of this multi-layered concept [84].

There is a generalization of the terms associated with personalized learning and a broad range of its scopes. The obstacles revealed in most of the studies examined in this review highlight the complexity and the need to primarily address technological and pedagogical issues to achieve more efficient and adaptive PL environments.

Other areas of opportunity for PL include designing strategies that address inclusion, educational policies, and institutional policies that can facilitate the successful implementation of these environments, as well as the need to establish a unified agreement on the implementation and essential components to plan a PL environment.

3.6. Correlational Analysis

Table 4 shows the correlation between Academic Level, Modality, Technology, and Barrier Categories, where the percentage indicates the proportion within the academic level category. These correlations reveal how different variables relate to each other in the context of personalized learning, showing specific patterns for each educational level.

Table 4. Results of the correlational analysis.

Academic Level	E-Learning	B-Learning	AI	OP	LMS	Technol.	Pedag.	Psychol.
Higher	63.60%	31.80%	59.10%	27.30%	31.80%	63.60%	40.90%	27.30%
Secondary	22.20%	66.70%	44.40%	55.60%	22.20%	44.40%	55.60%	33.30%
Elementary	12.50%	50.00%	50.00%	50.00%	12.50%	37.50%	50.00%	37.50%
Continuous	54.50%	27.30%	54.50%	36.40%	18.20%	54.50%	27.30%	18.20%

It is noteworthy that percentages are calculated concerning the total number of studies at each academic level. Also, some minor categories (such as Face-to-face, M-learning, other technologies and barriers) have been omitted for clarity, and finally, a study may use

multiple technologies or mention multiple barriers, so percentages in these categories may sum to more than 100%.

The analysis indicates that learning modality varies significantly by educational level. E-learning is predominant in higher and continuous education, whereas blended learning (B-learning) is more common in secondary and elementary education. The use of technology also follows distinct patterns: while artificial intelligence is widely employed at all levels, it is especially prominent in higher education. In contrast, other platforms are more evenly distributed across different educational levels. Additionally, Learning Management Systems are more frequently used in higher education, likely due to greater technological infrastructure in this sector.

Regarding barriers, we see that technological barriers are more frequent in higher and continuous education, while pedagogical barriers are more common in secondary and elementary education. Furthermore, psychological barriers seem to be more relevant in secondary and elementary education than at other levels.

The quantitative analysis of personalized learning implementation across various educational levels reveals significant correlations between academic level, learning modality, technology utilization, and encountered barriers. These correlations provide valuable insights into the diverse approaches and challenges in PL adoption across the educational spectrum.

In the realm of higher education, a distinctive pattern emerges, characterized by a predominant adoption of E-learning modalities and a pronounced utilization of artificial intelligence technologies. This predilection for E-learning, accounting for 63.6% of higher education studies, suggests a strong inclination towards digital and remote learning environments in tertiary education. Concurrently, the substantial employment of AI technologies (59.1%) in this sector indicates a trend towards sophisticated, data-driven personalization strategies. The prevalent use of Learning Management Systems in higher education, surpassing other educational levels, further corroborates the sector's inclination towards technologically advanced learning ecosystems. However, this technological emphasis is not without its challenges, as evidenced by the high frequency of technological barriers (63.6%) reported in higher education PL implementations.

Contrastingly, secondary and elementary education exhibit distinct characteristics in their approach to PL. In these sectors, Blended learning (B-learning) emerges as the predominant modality, with 66.7% of secondary education studies and 50.0% of elementary education studies employing this approach. This preference for B-learning may reflect an attempt to balance the benefits of technology-enhanced learning with traditional face-to-face instruction, particularly crucial for younger learners. Interestingly, these educational levels demonstrate a more balanced utilization of AI and Other Platforms, suggesting a diversified technological approach. However, unlike higher education, secondary and elementary levels report pedagogical barriers as the most frequent obstacle to PL implementation, with 55.6% and 50.0% respectively. This shift of primary barriers from technological to pedagogical as we move down the educational ladder underscores the varying challenges faced at different academic levels.

The landscape of continuous education presents yet another unique profile in PL implementation. While sharing similarities with higher education in terms of E-learning preference (54.5%) and AI utilization (54.5%), continuous education faces its own set of challenges. The high incidence of technological barriers (54.5%) in this sector mirrors the trend observed in higher education, suggesting that adult learners and professionals engaged in continuous education encounter similar technological hurdles in personalized learning environments.

Psychological barriers are prevalent across all educational levels, particularly in secondary and elementary education. This underscores the need to consider not only technological and pedagogical aspects but also the psychological factors that influence the success of personalized learning initiatives.

The implementation of personalized learning is not a one-size-fits-all approach but rather a complex interaction of educational level, learning modality, technology, and barriers. The varying patterns across educational sectors highlight the need for tailored strategies that address the unique challenges of each level. Future research should consider these distinctions to develop more effective and context-specific personalized learning strategies.

4. Discussion

The findings of this systematic literature review provide valuable insights into the current landscape of personalized learning implementation across various educational contexts, particularly concerning the role of artificial intelligence in facilitating PL. The results highlight the interplay between academic levels, learning modalities, technologies employed, and barriers encountered, demonstrating both the potential and challenges of AI-driven personalization in education. To better understand the broader implications, this discussion considers three key areas: the role of educators, the influence of policymakers, and the contributions of technology developers.

4.1. Implications for Educators

Educators play a central role in the effective implementation of PL approaches. The results of this study indicate that, while AI-based technologies offer powerful tools for adaptive instruction, teachers face significant pedagogical and psychological barriers. The adoption of AI in education requires educators to adapt their methodologies and integrate emerging technologies into their teaching practices. However, resistance to these new technologies often arises due to concerns regarding workload, motivation, and the perceived complexity of AI-driven systems. In addition, a lack of professional development programs tailored to the needs of educators further exacerbates the challenges associated with implementation.

Addressing these challenges requires the establishment of professional development initiatives that equip educators with the necessary digital and pedagogical skills to integrate AI tools effectively. In addition, institutions must provide sustained pedagogical support to assist teachers in designing personalized learning pathways that accommodate diverse student needs. Furthermore, fostering a culture that encourages experimentation with AI-driven personalization will contribute to overcoming psychological barriers and ensuring a smoother transition towards the adoption of AI-enhanced learning environments.

4.2. Implications for Policymakers

Policy decisions exert a profound influence on the scalability and sustainability of AI-driven PL implementations. The study findings reveal that institutional and infrastructural barriers, such as inadequate technological infrastructure, limited funding, and resistance to change, impede the adoption of PL models. These barriers are particularly evident in educational institutions that lack the necessary financial resources to invest in AI-compatible infrastructure and provide equitable access to personalized learning technologies.

To mitigate these challenges, policymakers must prioritize funding and infrastructure development to ensure that all institutions have access to the technological resources required for effective AI integration. Furthermore, the establishment of clear regulatory frameworks addressing data privacy, AI ethics, and teacher–student interaction in AI-mediated learning environments is essential for safeguarding the interests of both educators

and learners. In addition, policymakers should promote institutional adoption of AI-driven PL models by implementing policies that incentivize teacher training and encourage curriculum flexibility. By fostering a supportive regulatory environment, policymakers can contribute to the successful integration of AI in education while minimizing potential risks associated with its implementation.

4.3. Implications for Technology Developers

Technology developers play a crucial role in the advancement of AI-driven PL systems, as they are responsible for creating tools that are not only innovative but also accessible and pedagogically sound. The study highlights that, while AI offers advanced personalization capabilities, significant technological and ethical challenges persist, including user-friendliness, transparency, and data privacy concerns. These issues must be addressed to ensure that AI systems can be effectively adopted within educational settings without creating additional barriers for educators and students.

To enhance the usability of AI-driven PL tools, developers should prioritize user-centered design principles that consider the needs of both educators and learners. Ensuring that AI models offer clear explanations of their recommendations will improve transparency and foster greater trust in their use. Furthermore, strong privacy protections must be embedded within AI systems to safeguard student data and mitigate algorithmic biases that may disproportionately affect certain learner groups. Additionally, interdisciplinary collaboration between educators, policymakers, and developers is essential to creating AI-driven PL systems that are not only technologically advanced but also aligned with pedagogical objectives.

As a final insight, it is noteworthy to mention that the implementation of AI-driven personalized learning requires coordinated efforts among educators, policymakers, and technology developers. Educators must be empowered with the right skills and support structures, policymakers need to create enabling environments, and technology developers should ensure that AI tools are ethical, transparent, and user-friendly. While AI holds great promise for enhancing the personalization of learning experiences, significant challenges remain in terms of technological infrastructure, pedagogical adaptability, and psychological acceptance. The findings suggest that the effective implementation of AI-driven PL necessitates a nuanced approach that carefully balances technological innovation with pedagogical best practices. As institutions continue to explore the integration of AI in education, it is imperative to consider the diverse needs of learners and the structural constraints within educational systems. Future research should focus on long-term studies that assess the impact of AI-driven PL on student outcomes and engagement, as well as the development of AI systems designed to address the pedagogical and psychological barriers identified in this review. Ethical considerations, particularly regarding data privacy and algorithmic bias, must also remain central to discussions on the future of AI in education. Ultimately, a multidisciplinary and context-sensitive approach will be necessary to harness the full potential of AI-driven personalized learning in diverse educational settings.

4.4. Strategies to Overcome Challenges

To address the challenges identified in the results, a multifaceted approach is necessary. One key strategy involves investing in targeted professional development programs that focus on AI literacy and its pedagogical applications. These initiatives should be complemented by hands-on workshops where educators can experiment with AI tools in simulated classroom settings. Additionally, institutions must establish interdisciplinary teams comprising educators, AI specialists, and instructional designers to co-develop AI-integrated curricula tailored to diverse learning needs.

Beyond professional training, educational institutions must implement adaptive infrastructures that facilitate equitable access to AI-driven resources. Governments and private stakeholders should collaborate to create funding mechanisms that support schools with limited technological resources. Furthermore, ethical considerations in AI deployment must be embedded within institutional policies to ensure the fair and unbiased use of AI-driven learning systems. Transparency and explainability should be prioritized, allowing both educators and students to understand how AI-based recommendations are generated and applied.

However, counterarguments must be acknowledged. Some scholars argue that AI-driven personalization risks exacerbating existing inequalities by disproportionately benefiting institutions with greater financial and technological resources. Furthermore, concerns persist regarding AI biases, particularly in terms of racial and gender disparities, which may inadvertently disadvantage certain student groups. Critics also emphasize the irreplaceable role of human educators, warning against an overreliance on AI at the expense of human interaction and social–emotional learning.

While these concerns are valid, they do not necessarily negate the potential of AI in education. Instead, they highlight the need for continuous evaluation and improvement of AI systems to ensure fairness and inclusivity. Integrating human oversight within AI-driven PL models can help mitigate biases, as educators remain central in monitoring and interpreting AI-generated recommendations. Additionally, promoting open-source AI initiatives and cross-sector collaboration can help democratize AI access and reduce disparities between well-funded and under-resourced educational institutions.

Ultimately, the success of AI-driven PL depends on a holistic approach that balances technological innovation with ethical and pedagogical considerations. By fostering collaboration among educators, policymakers, and developers, and by maintaining a strong commitment to equity and human-centered learning, AI can serve as a powerful tool to enhance educational opportunities while preserving the essential role of human interaction in the learning process.

Funding: This research received no external funding.

Acknowledgments: We thank both Fundación Universidad de La Sabana (Group Technologies for the Academia—Proventus (EDUPHD-20-2022)) and Tecnológico de Monterrey for the received support in the preparation of this article.

Conflicts of Interest: The authors declare no conflicts of interest.

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