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Artificial intelligence and adaptive learning in education: Barriers, opportunities, and policy implications

Brigita Valeria Ledesma-Acosta[1], Gabriela Elizabeth Penafiel-Romero[2], Dennis Alfredo Peralta-Gamboa[3*]
[1,2,3]Universidad Estatal de Milagro, Milagro 091050, Ecuador; bledesmaa@unemi.edu.ec (B.V.L.A.), gpennafielr@unemi.edu.ec (G.E.P.R.), dperaltag2@unemi.edu.ec (D.A.P.G.).

Abstract: This research conducts a systematic literature review examining AI-driven adaptive learning systems and their deployment within educational environments. Drawing on 110 peer-reviewed sources retrieved from Scopus and Web of Science, the analysis investigates the ways these technologies foster individualized learning experiences, while pinpointing major advantages and substantial obstacles. The investigation focuses on three core dimensions: (1) technological and infrastructural obstacles impeding effective rollout, (2) the influence of such systems on learner motivation, involvement, and scholastic results, and (3) essential ethical issues, including algorithmic discrimination, protection of personal information, and system explainability. Results indicate reliable improvements in educational achievement, most notably in STEM fields and virtual learning settings, although they also expose serious concerns regarding access disparities and regulatory oversight. The article offers practical, implementable policy guidance and emphasizes the vital contributions of academic librarians, scholarly publishers, and educational technology providers in promoting ethical integration. Ultimately, the review stresses that multi-stakeholder partnerships, strong ethical guidelines, and equitable digital infrastructure are essential to realizing the full transformative capacity of AI-supported adaptive learning in a fair and enduring way.
Keywords: *Adaptive learning, Artificial intelligence in education, Learning personalization, Personalized education.*

1. Introduction

Education is among the many sectors that have been significantly transformed by artificial intelligence (AI) in recent years [1-3]. One of the most promising innovations in this field is the development of AI-powered adaptive learning systems, which aim to personalize instruction by responding to the unique needs of each student [4]. AI-powered adaptive learning systems rely on sophisticated algorithms [5] to process data on student performance [6], enabling real-time modifications to teaching materials, learning speed [7], and instructional approaches [5]. Unlike traditional one-size-fits-all methods, this individualized approach shows strong promise for boosting students' academic results and improving the quality of their overall learning journey.

Despite the documented benefits of adaptive learning technologies, several persistent barriers hinder their widespread implementation. Technological challenges such as algorithmic bias, limited interoperability, and insufficient infrastructure continue to complicate large-scale adoption. Furthermore, numerous educational institutions, especially in resource-constrained environments, often face shortages of essential funding, technical infrastructure, and administrative backing needed for the effective rollout of these technologies. Although the potential benefits of AI applications in education have received considerable attention in prior studies, few works offer a thorough examination of the real-world practical hurdles and ethical dilemmas involved in adoption, particularly in settings with restricted digital access and capacity.

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* Correspondence: dperaltag2@unemi.edu.ec

Understanding the elements that enable or hinder the adoption of adaptive AI tools is essential for transitioning these innovations from theory to widespread classroom use. The primary goal of this research is to provide policymakers and educational organizations with research-based, practical guidance by identifying major barriers to deployment and proposing targeted solutions. This work is particularly valuable in bridging the gap between advanced technological developments and their everyday implementation, ultimately fostering fairer and more effective integration of AI-enhanced adaptive learning methods. Additionally, the analysis emphasizes the urgent need to establish robust ethical guidelines that encourage responsible and thoughtful AI use within educational environments.

2. Literature Review

Recent literature consistently demonstrates the positive influence of AI-based adaptive learning systems on students' academic performance. A key systematic mapping by Ezzaim et al. [3] identifies deep learning methods, support vector machines (SVMs), and neural networks as the dominant algorithms employed in these platforms. Such techniques enable ongoing, responsive adjustments based on real-time student interactions, supporting personalized resource selection, predictive modeling of success, and dynamic reconfiguration of learning trajectories. This evolution has contributed to a shift from large-scale Massive Open Online Courses (MOOCs) toward more focused Small Private Online Courses (SPOs), which blend digital and face-to-face elements for greater customization.

Studies further illustrate practical benefits in engagement and outcomes. For instance, Lin and Lai [8] highlight how AI-driven precision education allows instructors to tailor content to individual learner needs, thereby increasing participation and achievement. In STEM contexts, Wu et al. [9] showcase the value of computer vision integration through their Real-time Automated STEM Engagement Detection System (RASEDS), which leverages deep learning models such as YOLOR to quantify student interaction levels in real time and adapt instructional delivery accordingly. This combination of AI and visual analysis proves highly effective for enhancing motivation and self-efficacy in complex scientific and technical subjects.

Complementary work by Demartini et al. [4] shows how merging machine learning with learning analytics enables real-time personalization of materials, helping educators detect struggling students early and adjust interventions holistically, including factors like motivation and involvement beyond mere grades. Naseer et al. [10] provide empirical evidence from a higher education setting in Pakistan, where an AI platform incorporating deep learning produced a 25% uplift in academic results compared to traditional methods, alongside notable gains in student participation. Deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have proven particularly valuable for processing performance data and enabling immediate content adaptations to better suit individual requirements (various studies).

Earlier contributions, such as those from Chen et al. [11] and Al-Chalabi et al. [12], reinforce the capacity of adaptive systems to boost engagement and long-term knowledge retention. More recent insights from Naseer et al. [10] extend these advantages to lifelong learning and professional development, indicating broad applicability across educational levels.

2.1. Objectives of the Study

The main goal of this research is to explore how AI-driven adaptive learning systems are being applied in various educational settings, assessing both the progress achieved to date and the key barriers limiting broader uptake. Through a structured literature review, the study seeks to identify current patterns in the deployment of these technologies, highlight factors that drive their effective use, and offer evidence-informed suggestions to facilitate stronger incorporation into teaching and learning practices.

2.2. Research Question

The three research questions guiding your systematic literature review on AI-powered adaptive learning systems are core. Based on your document's content, which heavily references sources like [3, 9, 10], and recent literature (2023–2025), here are concise, evidence-based answers. These can help strengthen or rewrite relevant sections (e.g., results, discussion, policy implications) by incorporating fresh synthesis while remaining faithful to the reviewed studies.

1. What are the primary technological and infrastructural obstacles that limit the effective rollout of AI-driven adaptive learning systems across diverse educational contexts?
2. In what ways do these adaptive systems influence student motivation, participation, and academic outcomes across various disciplines, with a particular focus on STEM fields and digital/online learning environments?
3. Which key ethical issues need to be resolved during the deployment of these systems, especially regarding biases embedded in algorithms, protection of student data privacy, and overall transparency?

3. Methodology

This research adopts a methodological approach based on a Systematic Literature Review (SLR) and bibliometric analysis to explore AI-powered adaptive learning systems and their implementation in educational settings, following the guidelines established by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol [13].

3.1. Databases Used

To guarantee the robustness and comprehensive coverage of the review, four prominent academic databases were chosen: Scopus, Web of Science (WoS), the Education Resources Information Center (ERIC), and Google Scholar.

Scopus and Web of Science stand out as leading multidisciplinary platforms, known for their selective curation of high-quality, peer-reviewed journals across a wide range of fields. Relying on these ensures the retrieval of reliable, rigorously vetted publications suitable for in-depth analysis.

ERIC was incorporated specifically for its specialization in education-related research and social sciences, granting access to specialized articles, government reports, and agency-produced materials that are highly relevant to pedagogical and instructional topics.

Google Scholar, with its more inclusive indexing approach, broadens the scope by capturing additional sources such as dissertations, conference proceedings, and repository-hosted documents, thereby supplementing the more curated results from other databases and reducing the risk of missing emerging or non-traditional outputs.

To prioritize influential and high-citation works within Web of Science, the review drew on the Social Sciences Citation Index (SSCI) and Science Citation Index Expanded (SCI-EXPANDED) subsets, which span publications dating back to 1975 and 1900, respectively. This strategy facilitated a thorough exploration of both social science perspectives and applied scientific contributions relevant to AI in education.

3.2. Definition of Search Equation

Database-specific search strings were developed to optimize retrieval. For Scopus, the query was applied as TITLE-ABS-KEY ("Automated Assessment" AND "Artificial Intelligence" AND "Education"). In Web of Science, the equivalent topic search was TS= ("Adaptive Learning" AND "Artificial Intelligence" AND "Education"). All queries were executed on September 11, 2024, retrieving records from the earliest indexed publications (1900 onward) up to the search date.

3.3. Inclusion and Exclusion Criteria Scopus:

The eligibility criteria for study selection were established as follows to balance breadth and methodological quality: (1) No restrictions were placed on subject disciplines, allowing for an interdisciplinary and wide-ranging review; (2) Only peer-reviewed publications in the form of journal articles, book chapters, and conference proceedings were retained to uphold scholarly standards; (3)

Materials in any language were eligible to promote inclusivity and capture global perspectives; and (4) Any documents published in 2025 or later were deliberately omitted, ensuring the focus remained on fully completed, peer-evaluated works available at the time of the search.

3.4. Bibliometric Analysis

The bibliometric component of this review encompassed several core dimensions to map the evolution and structure of research in this field:

- Productivity and citation trends
- Publication source evaluation
- Institutional and national contribution patterns
- Intellectual structure mapping

3.5. Tools Used

Data processing and visualization relied on RStudio (based on R version 4.4.1). The tidyverse package suite facilitated handling and analysis of metadata related to authors, journals, and countries. Network-based explorations, including author collaborations, co-citation patterns, and keyword co-occurrence for thematic insights, were conducted using VOSviewer (version 1.6.20).

4. Results

The search was conducted on February 27, 2025, yielding a total of 520 documents. A total of 52 duplicate records were removed. After screening titles and abstracts, 310 documents were excluded. Subsequently, access to the full text was not possible for 40 articles. Finally, after reviewing the available full-text documents, an additional 8 records were excluded (Figure 1).

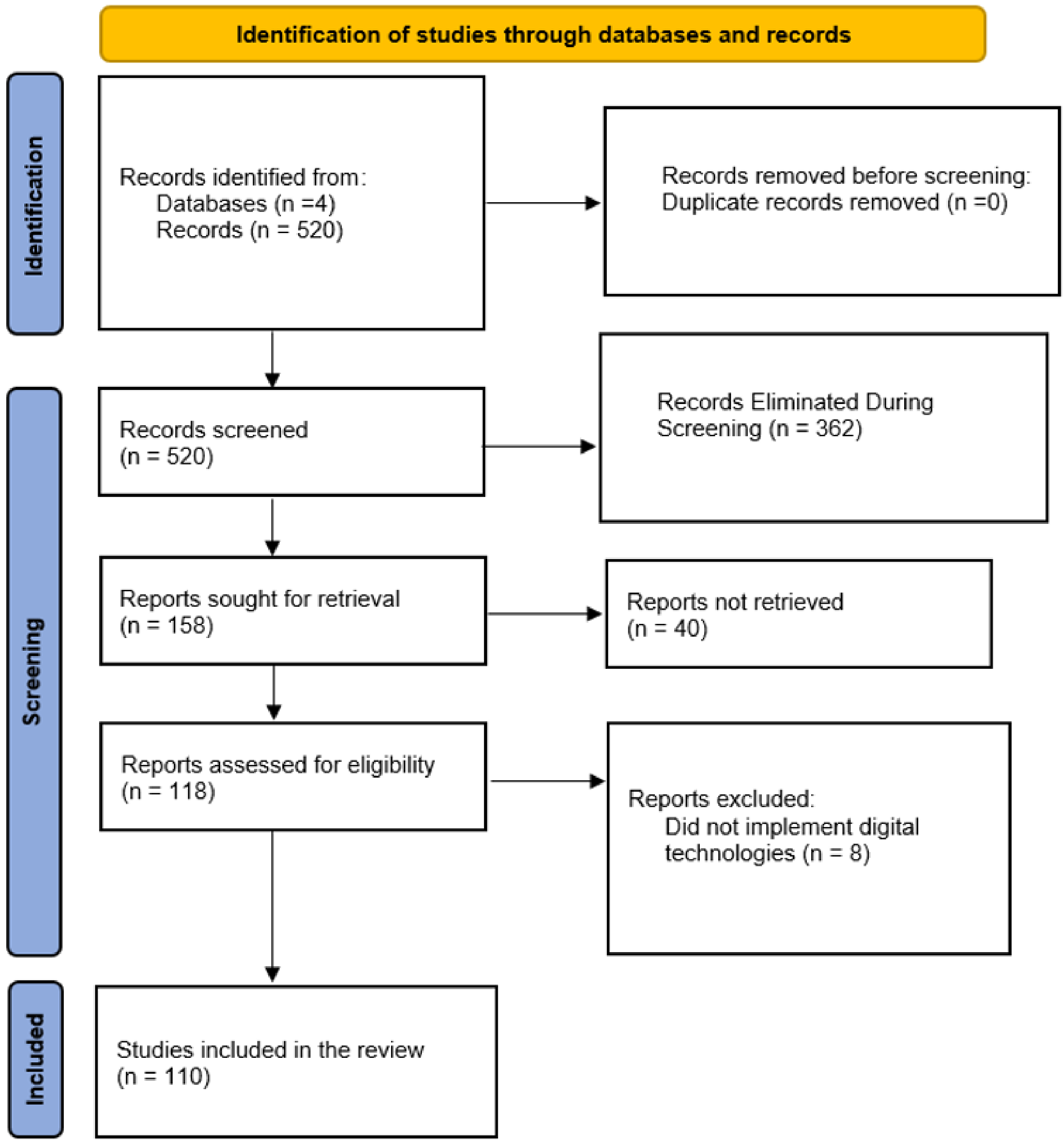

Figure 1.
PRISMA Selection Process.

The bibliometric analysis was organized around four principal dimensions to provide a comprehensive overview of the research landscape on this topic. It began with an examination of publication output and citation patterns to highlight the most productive authors and the most influential documents. This was followed by an assessment of key publication venues, including the journals and conference proceedings that have been most active in disseminating work in the field. The analysis also mapped contributions from leading institutions and countries, revealing patterns of international research activity. Finally, the intellectual structure was explored through network visualizations, encompassing author co-citation relationships, institutional collaboration links, and keyword co-occurrence clusters to uncover thematic trends and interconnections.

4.1. Productivity Analysis

The examination of publication and citation trends over time reveals a clear acceleration in research activity in recent years (see Figure 1). Prior to 2022, output remained modest, typically ranging from 1 to 3 documents annually; for instance, only 2 publications appeared in 2013 and 1 in 2014, reflecting limited attention to the topic during that period.

From 2022 onward, however, the number of publications rose sharply, culminating in a high of 18 documents in 2024. This surge indicates growing scholarly interest and expanded production in the domain of AI-powered adaptive learning.

Regarding citations, an intriguing pattern emerges: even though 2024 saw the highest volume of new papers, those published in 2022 garnered the greatest cumulative citations (205 in total), indicating that earlier works from that year exerted substantial influence within the research community. Similarly, the 3 documents from 2017 amassed 131 citations, a strong showing relative to their low count, underscoring their lasting relevance. Years with minimal output, such as 2014 and 2018, still generated moderate citation levels, demonstrating that quality publications from quieter periods were not overlooked. In 2023, with 13 publications, citations reached 118, a robust figure suggesting strong reception of that year's contributions.

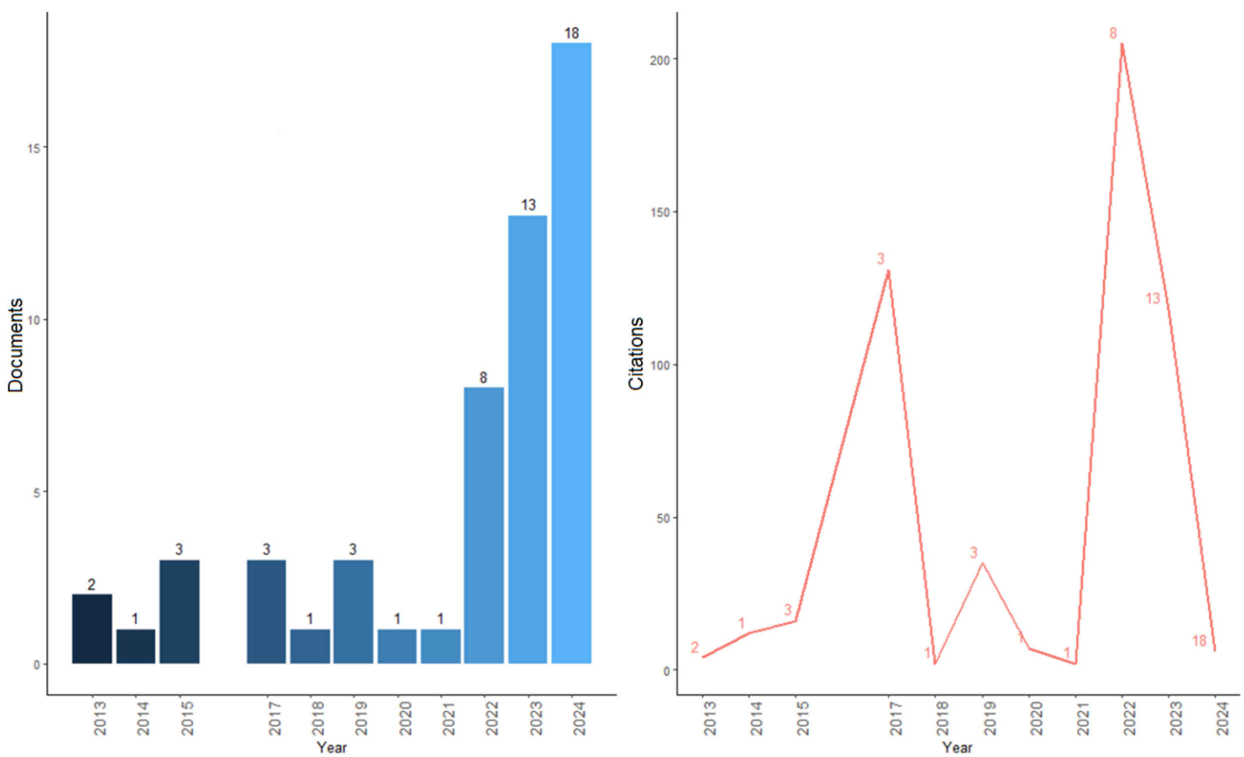

Figure 2.
Annual Evolution of Documents and Citations (2013-2024).

4.2. Journal Analysis

Publications on AI-powered adaptive learning systems and their educational applications appeared in 45 distinct journals and conference series. The most prominent outlets in terms of publication volume are summarized in Table 1, while Table 2 ranks those with the strongest citation impact.

Table 1 identifies the top 10 sources by the number of documents. CEUR Workshop Proceedings and Lecture Notes in Computer Science lead with 4 papers each, underscoring the central role of conference proceedings and workshop collections in advancing research on this emerging topic. These venues are well-known for hosting cutting-edge discussions on innovative technologies and their integration into education, aligning perfectly with the field's rapid development and interdisciplinary character.

Communications in Computer and Information Science ranks next with 3 contributions, reinforcing the importance of this area within computing and information sciences, particularly regarding AI applications for teaching and learning.

The International Journal of Artificial Intelligence in Education features 2 papers, highlighting its specialized focus on AI-driven educational innovations and its growing prominence over the past decade.

Other sources, including Proceedings of MIPRO 2024, ACM International Conference Proceedings, and AIP Conference Proceedings, each contributed 1 paper. Despite lower volume, these reflect meaningful participation from specialized international events at the intersection of education, advanced computing, and AI-enhanced instruction.

Overall, this distribution indicates that much of the discourse on adaptive learning systems occurs within conference-oriented outlets and proceedings series in information technology and education. This pattern reflects the field's dynamic, emerging status and its deep ties to technological innovation and pedagogical advancement.

Table 1.
Sources with the Highest Number of Documents.

Magazine	Documents
CEUR Workshop Proceedings	4
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial…	4
Communications in Computer and Information Science	3
International Journal of Artificial Intelligence in Education	2
2024 47th ICT and Electronics Convention, MIPRO 2024 - Proceedings	1
2024 4th International Conference on Advanced Computing and Innovative Techno…	1
ACM International Conference Proceeding Series	1
AIP Conference Proceedings	1
AMIA ... Annual Symposium proceedings / AMIA Symposium. AMIA Symposium	1
ASEE Annual Conference and Exposition, Conference Proceedings	1

Table 2 ranks the publication sources by total citations received, indicating their influence within the scholarly community on AI-powered adaptive learning and educational implementation.

TechTrends leads with 126 citations, emerging as the most impactful outlet. Its emphasis on innovative educational technologies explains this top position, as the journal has likely featured seminal works on AI integration in adaptive systems that have been frequently referenced across the field.

Sustainability (Switzerland) ranks second with 87 citations, indicating a growing focus on adaptive AI from the perspective of long-term educational viability and resource-conscious innovation. This reflects broader efforts to align technological advancements with sustainable pedagogical goals.

The DIS 2017 - Proceedings of the 2017 ACM Conference on Designing Interactive Systems has 82 citations, highlighting the importance of human-centered design and interactive interfaces in developing AI-driven adaptive tools. The high citation count emphasizes the value placed on user experience and interaction design within educational AI research.

The International Journal of Artificial Intelligence in Education contributes 46 citations, confirming its status as a cornerstone for specialized scholarship at the intersection of AI and learning processes. Its dedicated focus continues to make it a go-to resource for foundational and applied studies in this domain.

Additional sources with notable but lower impact include Medical Teacher (25 citations) and Brain Communications (16 citations). Though not primarily centered on education or AI, their involvement demonstrates how adaptive learning concepts extend into medical training and neuroscientific applications, illustrating the topic's cross-disciplinary reach.

Venues such as Lecture Notes in Computer Science, AMIA Symposium Proceedings, and the European Journal of Education show more moderate citation totals (11–13 each), suggesting valuable but less dominant contributions compared to the leading sources.

Taken together, the citation leaders reveal that research on adaptive learning systems draws from diverse lenses, including interactive system design, sustainability in education, specialized AI-education journals, and specialized domains, underscoring the field's highly interdisciplinary scope and wide applicability across technological, pedagogical, and societal contexts.

Table 2.
Sources with the greatest impact on the scientific community.

Magazine	Citations
TechTrends	126
Sustainability (Switzerland)	87
DIS 2017 - Proceedings of the 2017 ACM Conference on Designing Interactive S…	82
International Journal of Artificial Intelligence in Education	46
Construction Innovation	26
Medical Teacher	25
Brain Communications	16
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial…	13
AMIA ... Annual Symposium proceedings / AMIA Symposium. AMIA Symposium	12
European Journal of Education	11

4.3. Contribution of Institutions and Countries

The analysis of the academic collaboration network illustrated in Figure 1 shows the connections between various universities and institutions on the topic of AI-powered adaptive learning systems and their implementation in educational environments.

4.4. Main Groups and Collaborations

The collaboration network visualized in Figure 1 reveals patterns of institutional partnerships in research on AI-powered adaptive learning systems and their educational applications.

A prominent, tightly interconnected cluster appears on the left, dominated by institutions such as the University of North Carolina, Humboldt University of Berlin, and Free University of Berlin. These entities form a central hub, suggesting frequent joint publications and strong collaborative ties that have driven much of the advancement in this domain.

This main cluster extends to include additional partners such as the University of Brasília and the Berlin Institute of Health, along with healthcare-related organizations like Rhode Island Hospital. The presence of non-academic and medical institutions within the network indicates cross-sector applications of adaptive learning technologies, extending beyond traditional classroom settings into areas like professional training and health sciences education.

4.5. International Connections

At the center of Figure 1, the University of Pisa emerges as a pivotal connector, linking the core cluster to more peripheral nodes, including Tuscia University and smaller entities. Positioned as a key intermediary, it facilitates knowledge exchange across diverse groups, bridging research communities in countries such as Brazil, Italy, Germany, and the United States. This central role likely positions the University of Pisa as an influential node in global efforts on the topic.

Figure 2 further emphasizes leadership dynamics within the network. Institutions like the Free University of Berlin and the University of North Carolina exhibit extensive connections, reflecting their prominent roles in steering research directions on adaptive systems.

Conversely, the University of Pisa functions as a critical bridge among clusters, enabling the flow of ideas across geographic and disciplinary boundaries. The integration of hospitals and healthcare entities

in the network underscores the field's interdisciplinary character, with potential extensions to medical education, clinical training, and other specialized domains.
The country collaboration network presented in Figure 3 illustrates the international partnerships driving research on AI-powered adaptive learning systems and their educational deployment.
The United States dominates as the largest node, with 27 documents, underscoring its leading position in both productivity and influence. The extensive links emanating from this node reflect widespread collaborations with institutions worldwide, positioning American research centers as central drivers of knowledge generation and dissemination in the field.
China emerges as a major secondary hub, connected strongly to the United States and contributing 10 publications. This prominent placement highlights China's substantial and growing involvement in AI applications for education, often through joint efforts with leading American and other international teams, contributing significantly to technical and methodological advances in adaptive systems.

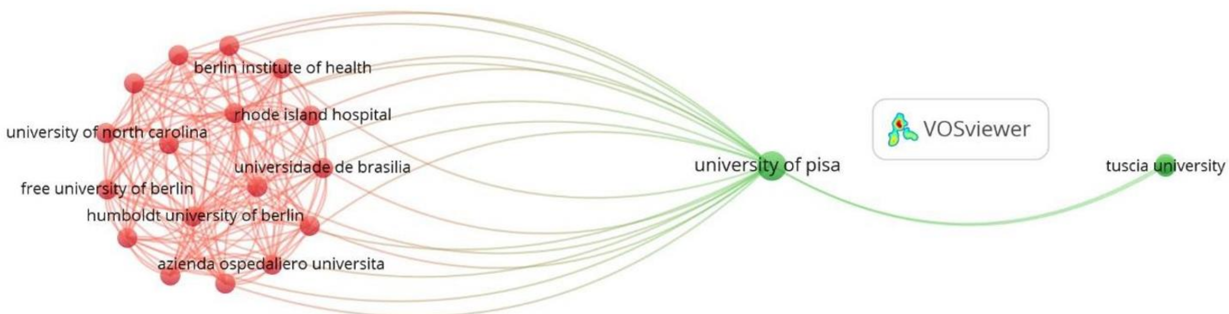

Figure 3.
Institutional Collaboration Map based on VOSviewer.

Hong Kong appears as a smaller but notable node, linked primarily to China, indicating focused regional collaboration within the broader East Asian context. Its inclusion signals the rising contribution of Hong Kong-based research to educational technology development, particularly in AI-enhanced learning environments.

Figure 2 complements this view by emphasizing the strength of cross-border ties: the United States maintains the widest network of connections, while China's involvement reinforces a key bilateral axis. Hong Kong's specialized position within this framework further illustrates targeted cooperation.

Collectively, the network demonstrates that progress in adaptive AI for education is a truly international endeavor, with major technological leaders like the United States and China at the forefront, supported by regional contributors. This global distribution indicates shared momentum in addressing educational challenges through AI, offering opportunities for even broader participation from emerging research regions.

4.6. Analysis of the Intellectual Structure

Figure 4 presents a keyword co-occurrence network that maps core concepts and thematic interconnections in the literature on AI-powered adaptive learning systems.

Artificial intelligence (AI) dominates as the most prominent and centrally positioned term, underscoring its foundational role in linking diverse strands of research. Its size and central placement highlight how AI serves as the unifying thread across studies, fundamentally reshaping educational methodologies through intelligent, data-responsive mechanisms.

Figure 4.
International Collaboration Network.

Closely linked to AI are terms like machine learning and adaptive learning, which form strong clusters and emphasize reliance on algorithmic techniques to enable dynamic, student-centered personalization of content and pacing.

Other notable connections include virtual reality, chatbots, and online learning, illustrating the integration of immersive, conversational, and digital platforms to enrich interactive and remote educational experiences.

The presence of natural language processing and ChatGPT further emphasizes the growing importance of language-based AI for facilitating more intuitive student-system dialogues and feedback loops.

The education node stands out with extensive ties to multiple areas, reflecting the pervasive application of these technologies across teaching and learning contexts—not just for tracking progress but for tailoring experiences holistically.

Terms such as assessment, formative assessment, and project-based learning appear prominently connected, signaling focused attention on how AI can refine evaluation methods, provide real-time insights, and support experiential, competency-driven approaches in educational settings.

Overall, this network visualization captures the field's thematic richness, with AI at the core orchestrating a convergence of computational tools, pedagogical strategies, and emerging digital modalities to advance personalized education.

4.7. Interdisciplinary Connections

The network in Figure 4 also reveals clear links between artificial intelligence and specific educational subfields, including educational psychology, classroom management, and mathematics instruction. These associations demonstrate that AI's role extends well beyond purely computational or engineering applications, penetrating deeply into psychological theories of learning, practical strategies for classroom dynamics, and subject-specific pedagogical approaches. This broad connectivity reinforces the inherently interdisciplinary character of the research, where AI tools are being adapted to support cognitive processes, behavioral management, and domain-focused instruction rather than remaining limited to generic technology deployment.

4.8. Technological Innovation

The keyword map in Figure 4 also uncovers connections between artificial intelligence and specialized technologies such as virtual reality, computer-based simulations, and robotics. These links illustrate a clear movement toward immersive and interactive tools that enrich educational experiences by enabling realistic, hands-on scenarios and responsive learning environments.

Such integrations point to a broader shift in the literature, where cutting-edge digital innovations are being harnessed to foster more engaging and experiential instruction. The map as a whole conveys the field's expansive interdisciplinary scope: it spans targeted applications in educational psychology, classroom organization, and mathematics pedagogy, while incorporating advanced computational approaches like natural language processing. The recurring prominence of core concepts, machine learning, adaptive learning, and artificial intelligence underscores their indispensable role in redefining modern educational practices, from individualized pathways to technology-supported classroom dynamics.

5. Discussion

A comprehensive review of the literature reveals that, despite rapid growth in the field, widespread adoption of AI-driven adaptive learning systems remains constrained by persistent barriers.

Key obstacles include technological and infrastructural shortcomings, particularly in resource-limited settings. Many institutions struggle with unreliable internet access, inadequate devices, and legacy systems that hinder integration [14]. Compatibility issues between existing learning platforms and AI tools further complicate deployment [15], compounded by insufficient professional development for educators and staff to effectively incorporate these technologies into teaching [16]. High ongoing costs for maintenance and updates add additional strain. Algorithmic biases arising from unrepresentative training data also risk perpetuating unfair outcomes, limiting true personalization, and widening disparities.

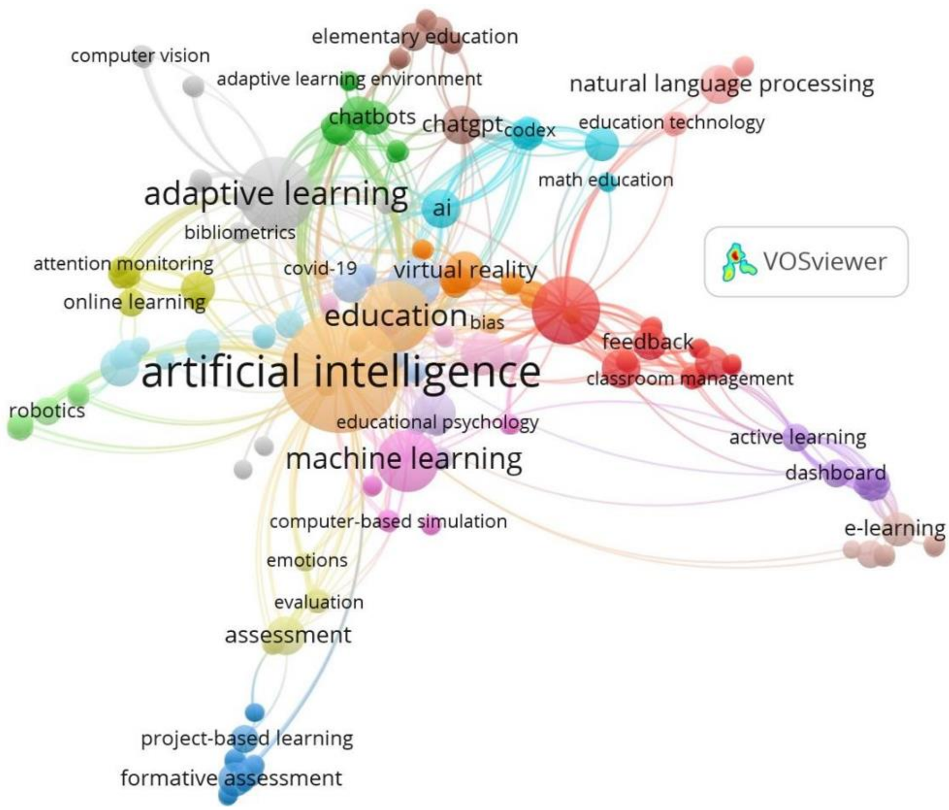

Figure 5.
Keyword Network Visualization.

Notwithstanding these hurdles, evidence points to substantial benefits for student engagement and academic success. In STEM disciplines, real-time engagement monitoring systems like RASEDS enable adaptive instruction that boosts motivation and confidence [9]. Personalized pathways powered by deep learning in higher education have yielded performance improvements of up to 25% compared to traditional methods [10]. Adaptive approaches in small private online courses (SPOCs) and massive open online courses (MOOCs) have lowered dropout rates and strengthened retention [8]. Integration of virtual reality with AI supports hands-on, inquiry-driven learning in technical subjects, offering enhanced experiential opportunities [17].

These findings suggest that, while challenges persist, targeted efforts to address infrastructure, training, bias mitigation, and accessibility could unlock the full potential of these systems across diverse educational contexts.

5.1. Ethical Considerations in AI-Powered Education

Ethical deployment of AI-powered adaptive learning systems in education demands careful consideration of multiple interconnected issues beyond just bias and privacy.

1. Fairness and Algorithmic Discrimination — Models in educational AI frequently draw from historical data that encode existing inequities. Without diverse, representative training sets, these systems can reinforce disadvantages, for example, by inaccurately predicting needs or potential for students from underrepresented groups [18]. Addressing this requires proactive measures: technical debiasing techniques, inclusive dataset curation, and collaborative design processes that incorporate input from educators and varied student communities.

2. Protection of Student Data and Security — These platforms gather detailed information on performance, behaviors, and affective states, creating significant risks if data handling lacks transparency or robust safeguards. Adherence to standards like GDPR (Europe) or FERPA (U.S.) is necessary but often insufficient alone. Responsible practice requires clear privacy policies, meaningful informed consent, minimization of collected data, secure storage, and strict controls on sharing or transfer [15].

3. Interpretability and Accountability — Many AI algorithms operate as opaque "black boxes," making it difficult for teachers or learners to understand the reasoning behind automated suggestions or assessments. Explainable AI approaches aim to render these processes comprehensible, fostering trust and enabling oversight. For example, when a system proposes additional support for a student, both educators and the learner should be able to grasp the underlying factors and logic.

4. Preserving Learner Independence and Avoiding Excessive Dependence — While personalization is a strength, heavy reliance on automated systems can erode students' self-direction, creativity, and critical reasoning skills. Overly authoritative AI feedback may limit experimentation, and substituting human interaction with machine-generated guidance risks weakening the relational, motivational aspects of teaching. Ethical implementation should position AI as a supportive tool that enhances, rather than supplants, human judgment and teacher-student relationships.

5. Access Equity and Bridging the Digital Divide — Structural barriers to technology access must be confronted, as students in low-resource settings may be excluded from the benefits of these systems, thereby deepening existing gaps. Ethical guidelines must prioritize universal design principles, digital inclusion initiatives, and commitments to equitable distribution of AI-enhanced resources across socioeconomic and geographic lines.

5.2. Relevance for Librarians, Publishers, and Educational Stakeholders

Although this study primarily focuses on the educational applications of AI-powered adaptive learning systems, its findings also have important implications for a broader set of stakeholders, including academic librarians, publishers, edtech developers, and institutional decision-makers.

5.3. Academic Librarians

Librarians serve as essential contributors to the successful integration of adaptive learning ecosystems powered by AI, fulfilling several strategic functions:

- Selecting and organizing high-quality digital resources that can be ingested into adaptive platforms, prioritizing peer-reviewed, inclusive, and varied materials to support effective algorithmic recommendations.
- Overseeing institutional access to AI-enhanced educational resources through subscriptions and licensing agreements, promoting fair distribution so students from all disciplines can benefit without barriers.

- Delivering training programs on AI literacy for students and faculty, emphasizing responsible data handling, advanced digital search techniques, and critical assessment of AI-produced outputs.
- Collaborating on the creation and refinement of metadata frameworks that enable seamless machine processing and incorporation into personalization engines (for example, by applying structured tags to open educational resources to improve discoverability and adaptive matching).

5.4. Academic Publishers

Publishers are well-positioned to capitalize on the expansion of adaptive learning technologies by pursuing the following strategic opportunities:

- Creating flexible, structured educational materials that are easily parsed by machines, such as using formats like XML or structured markup for learning objects, enabling seamless incorporation into AI-driven personalization engines.
- Launching or expanding companion digital tools that provide adaptive assessments, interactive exercises, or supplementary platforms tightly aligned with their published textbooks, examples include similar efforts by publishers such as Springer and McGraw-Hill with ALEKS.
- Partnering with academic researchers, edtech developers, and content specialists to build specialized training resources, such as curated datasets, interactive simulations, or domain-focused repositories, that help improve the accuracy and relevance of AI models in delivering subject-specific instruction.

5.5. Educational Technology Providers and Policymakers

For developers of educational technology and policymakers, this review offers several practical insights:

- A clear framework for designing AI tools that align with ethical guidelines, pedagogical priorities, and infrastructural realities of schools and universities.
- Identification of promising avenues for cross-sector partnerships, where government education agencies, technology vendors, and content creators jointly build interoperable and inclusive digital platforms.
- Reinforcement of the benefits of adopting open technical standards and strong data governance models, which facilitate secure and compliant incorporation of external AI solutions into broader national or institutional education policies.

Involving these stakeholders more actively in both the conversation and the rollout of adaptive learning technologies substantially boosts the likelihood of achieving adoption that is sustainable, fair, and grounded in ethical principles.

The surge in scholarly attention to AI applications in education since 2022 is evident in the marked rise in publication volume and the diversification of research themes. For example, Hadzhikolev et al. [19] advanced evaluation techniques using neural networks and support vector machines to assess advanced cognitive skills, underscoring AI's expanding role in sophisticated assessment. This aligns with Kamalov et al. [20], who described how generative tools like ChatGPT enable large-scale personalization and data-driven insights, fundamentally reshaping instructional design. As these innovations mature, they are increasingly embedded in institutional practices [21] fueled by the availability of user-friendly AI platforms for automated grading, intelligent tutoring, and real-time support. Recent analyses, including Šumak et al. [22], document this acceleration between 2022 and 2024.

Machine learning techniques [14, 23] and natural language processing advancements [24] have become central to achieving effective personalization, with multiple studies confirming substantial gains in retention and performance from individualized approaches [20]. Complementary evidence from King et al. [17] shows how AI-integrated virtual reality supports self-directed practice and refined instructional delivery, pointing to AI's capacity to elevate learning quality.

The proliferation of specialized conferences and journals dedicated to AI in education further signals the field's interdisciplinary nature. Outlets such as CEUR Workshop Proceedings and Lecture Notes in

Computer Science serve as primary venues for adaptive learning research [25, 26]. Earlier contributions, such as Leeman-Munk et al. [27], demonstrated how deep learning and topological approaches can analyze student-created content like writing and artwork, illustrating AI's enhancement of experiential and creative learning.

International collaboration has proven vital to progress in this domain. Examples include Zheng et al. [28] in China, who used AI knowledge graphs to improve group dynamics and shared regulation in collaborative settings, and King et al. [17] in the United States, who validated intelligent virtual reality for mathematical skill-building. Parallel efforts in other contexts [29, 30] reinforce the value of cross-border initiatives in advancing adaptive technologies.

AI also contributes meaningfully to educator preparation, even as it enhances university-level instruction [15], delivers instant feedback to learners, and equips them for professional demands. King et al. [31] showed how AI-driven virtual reality can refine instructors' questioning techniques in mathematics, automating aspects of professional development. Owan et al. [32] further noted AI's role in strengthening assessment practices, including formative and project-based evaluations, allowing teachers to adjust strategies dynamically.

Despite clear advantages, adaptive systems face ongoing limitations. Resource shortages—both human and technological- persist in many institutions [16]. Regulatory environments that fail to encourage investment restrict progress [33]. Algorithmic bias and inadequate training data remain concerns in diverse student populations [18], while ethical dilemmas around bias and privacy continue to slow uptake [15]. Technical issues, such as limitations in speech processing and response flexibility, also endure [31].

Future efforts should prioritize resolving these technical, institutional, and funding barriers. International cooperation will be crucial for establishing ethical and regulatory frameworks that promote responsible AI use in education, as emphasized by Pan et al. [29] and Cedeno et al. [15].

5.6. Policy Suggestions

To overcome the barriers outlined in this review and promote effective, equitable rollout of AI-powered adaptive learning systems, the following policy directions are recommended, each including practical steps and illustrative examples:

1. Upgrading digital infrastructure: national and institutional leaders should prioritize digital modernization, especially in underserved and rural areas. Key actions include:

- Distributing low-cost, AI-ready devices (e.g., Chromebooks, tablets, or low-spec laptops) pre-installed with proven adaptive platforms such as Century Tech, Smart Sparrow, or Knewton Alta.
- Launching large-scale connectivity initiatives to deliver stable broadband to remote and low-income schools.
- Shifting toward lightweight, cloud-hosted solutions (e.g., Khanmigo, Socrative AI Tutor, or similar low-resource tools) that reduce dependence on powerful local hardware.

2. Establishing Ethical and Governance Standards Policymakers should collaborate with AI specialists, ethicists, educators, and legal experts to develop clear regulatory guidelines that cover:

- Explicit consent procedures and full transparency about data collection and usage, aligned with international standards such as GDPR or FERPA.
- · Required algorithmic audits and fairness reviews as mandatory components of public procurement processes for AI education tools.
- · Uniform requirements for explainability and interpretability across all adopted platforms to ensure accountability and trust.

3. Building Educator Capacity and Ongoing Support. Effective adoption hinges on well-prepared teachers. Recommended measures include:

- Creating national credentialing or certification pathways focused on educational technology and AI competencies (e.g., inspired by programs like Microsoft's AI for Educators).
- Organizing hands-on professional learning sessions using simulation-based environments (e.g., ClassVR, Labster, or comparable virtual labs) to build confidence in using adaptive tools.
- Setting up peer-support networks or mentorship programs where experienced edtech practitioners guide colleagues in integrating AI into daily practice.

4. Fostering Global and Regional Partnerships. To accelerate innovation and address resource disparities, policies should encourage:

- Funding for joint research and development projects on AI in education, such as through programs similar to Erasmus+ EdTech calls or bilateral agreements.
- Piloting cross-border virtual classrooms or shared adaptive platforms to test tools across cultural and linguistic boundaries.
- Creating international monitoring bodies or observatories that track AI education trends and disseminate best practices through regular reports and open-access resources.

5. Advancing Equity and Universal Access. Ensuring all learners can benefit requires deliberate inclusion strategies, such as:

- Forming public-private alliances to subsidize devices, connectivity, and software licenses for economically disadvantaged communities.
- Mandating built-in accessibility features in all approved adaptive platforms (e.g., screen readers, text-to-speech, adjustable fonts, multilingual interfaces).
- Conducting regular national audits to identify and close gaps in AI adoption, focusing on reducing the digital divide.

6. Establishing Ongoing Monitoring and Improvement Mechanisms. Continuous evaluation is essential for refinement and accountability. Suggested actions include:

- Deploying real-time analytics dashboards that provide actionable insights to teachers and school leaders.
- Embedding user feedback loops within platforms (e.g., end-of-session surveys, hybrid AI-human reflection tools).
- Requiring annual or biennial evaluations of AI system impact on student outcomes, with results used to update implementation guidelines.

6. Conclusion

This systematic review highlights the substantial potential of AI-driven adaptive learning systems to reshape education by delivering more personalized, engaging, and effective experiences, particularly in STEM subjects and virtual settings. It also clarifies that scaling these technologies faces serious roadblocks related to infrastructure deficits, ethical risks, and unequal access.

Overcoming these barriers calls for purposeful, multi-layered action. Governments and institutions must invest in robust digital foundations, close access gaps, and equip teachers with targeted AI training. Equally critical is the establishment of strong governance structures that safeguard student privacy, ensure algorithmic fairness, and promote transparency in automated decision-making. The review also emphasizes the vital supporting functions of academic librarians in curating accessible digital collections and fostering AI literacy, as well as the contributions publishers can make through structured, adaptable content and integrated assessment resources.

In the end, realizing the long-term value of adaptive learning technologies will require sustained cooperation among educators, technologists, policymakers, and knowledge organizations. Through inclusive design processes, continuous monitoring, and shared commitment to equity and ethics, these systems can be positioned to meet tomorrow's educational demands while upholding the core principles of quality, fairness, and human-centered learning.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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