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Systematic Review

The Impact of Artificial Intelligence on Personalized Learning in Higher Education: A Systematic Review

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Abstract: The integration of artificial intelligence in education has the potential to revolutionize personalized learning by adapting instructional methods, content, and pace to the individual needs of students. This systematic review investigates the integration of artificial intelligence into personalized learning within higher education. An extensive literature search was conducted across multiple databases, yielding 17,899 records from which 45 studies met the inclusion criteria. The risk of bias was assessed using a standardized ranking system. This systematic review follows the PRISMA guidelines to ensure transparency in study selection, data extraction, and synthesis. The findings of the review are synthesized to examine how AI-driven solutions enhance adaptive learning, improve student engagement, and streamline administrative processes. The results indicate that AI technologies can significantly optimize educational outcomes by tailoring content and feedback to individual learner needs. However, several challenges persist, such as ethical concerns, data privacy issues, and the necessity for effective teacher training to support technology integration. This analysis reveals considerable potential for AI to transform educational practices, while also emphasizing the importance of establishing standardized evaluation frameworks and conducting longitudinal studies. The implications of these findings are critical for educators, policymakers, and university administrators aiming to leverage AI for educational innovation and sustainable transformation.

Keywords: intelligent tutoring systems; adaptive learning environments; data-driven education; learning analytics; educational innovation

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1. Introduction

Over the past decade, artificial intelligence (AI) has emerged as a transformative force across various sectors, notably in education [1]. AI's capacity to analyze extensive datasets and adapt to individual needs has paved the way for personalized learning approaches. These approaches aim to tailor content, pacing, and instructional methods to each student's unique characteristics, thereby fostering more effective and meaningful educational experiences [2].

AI facilitates the development of adaptive learning environments that respond in real-time to student progress and challenges. For instance, intelligent tutoring systems can identify areas needing improvement and provide targeted resources to address detected deficiencies [3]. Moreover, AI-driven educational platforms can collect and analyze data on student performance, enabling educators to make informed decisions to enhance their teaching [4].

However, integrating AI into education presents significant challenges. Addressing ethical concerns related to student data privacy, equitable access to these technologies, and the necessity of training educators in the effective use of AI-based tools is of paramount importance. Addressing these challenges is crucial to ensure that AI enhances educational capabilities without supplanting the fundamental role of educators [5].

The focus of this study is situated within a higher-education context, examining how AI-driven solutions can foster personalized learning experiences in universities and other post-secondary institutions. By emphasizing both the opportunities and challenges, this paper seeks to provide insights relevant to educators, policymakers, and university administrators seeking to harness AI for educational innovation. This review is guided by the following research question: How does AI impact personalized learning in higher education?

Despite increasing interest in AI-driven educational tools, the existing literature lacks a comprehensive synthesis of empirical findings across diverse learning environments. This systematic review aims to bridge this gap by evaluating the effectiveness, ethical considerations, and practical challenges of AI in personalized learning at the postsecondary level.

2. Materials and Methods

This study was conducted through a systematic literature review, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a transparent and replicable research process [6]. The objective was to identify and analyze relevant research on the impact of AI in personalized learning.

A systematic review was conducted following guidance from prior research practice by Kitchenham [7], with searches performed across several academic databases, including Google Scholar, Web of Science, Scopus, ERIC, and PubMed. The search was executed in February 2025, and the search terms for this literature review were derived from prior searches conducted by Essa et al. [8] and Rangel-de Lazaro and Duart [9] with certain modifications specifically tailored to the scope of this review.

This systematic review has been registered in PROSPERO, an international prospective register of systematic reviews.

2.1. Eligibility Criteria

Studies were included if they (1) were published between January 2023 and 2025; (2) focused on the application of AI in higher education with a specific emphasis on personalized learning; (3) were published in peer-reviewed journals; (4) contained empirical data; and (5) were available in English.

The exclusion criteria included (1) studies not directly related to AI in personalized learning, (2) theoretical articles without empirical support, (3) non-peer-reviewed studies, and (4) studies focusing on primary or secondary education.

2.2. Information Sources and Search Strategy

The search strategy was meticulously designed to identify relevant studies using Boolean operators and keywords. Specific search strings were adapted to each database, as shown in Table 1. Filters were applied to include only peer-reviewed articles and exclude non-empirical studies such as opinion pieces, editorials, and conference abstracts.

Table 1. Literature review sources: search databases, strings, and number of results.

Database	Search String	Results
PubMed	(“artificial intelligence” OR “AI”) AND (“personalized learning” OR “adaptive learning”) AND (“education” OR “teaching” OR “students”) AND (“higher education”)	10

Table 1. *Cont.*

Database	Search String	Results
Scopus	TITLE-ABS-KEY("artificial intelligence" OR "AI") AND TITLE-ABS-KEY("personalized learning" OR "adaptive learning") AND TITLE-ABS-KEY ("education" OR "teaching") AND TITLE-ABS-KEY ("higher education")	328
Web of Science	TS = ("artificial intelligence" OR "AI") AND TS = ("personalized learning" OR "adaptive learning") AND TS = ("education" OR "teaching" OR "students") AND TS = ("higher education")	107
ERIC	("artificial intelligence" OR "AI") AND ("personalized learning" OR "adaptive learning") AND ("education" OR "teaching") AND ("higher education")	54
Google Scholar	("artificial intelligence" OR "AI") AND ("personalized learning" OR "adaptive learning") AND ("education" OR "teaching") AND ("higher education")	17,400
Total		17,899

This comprehensive search process yielded a total of 17,899 articles, which were subsequently screened to identify studies that met the inclusion criteria for the systematic review.

2.3. Study Selection Process

The study selection process involved multiple steps to ensure a rigorous and transparent review. Initially, duplicate records were removed using reference management software. Subsequently, titles and abstracts were screened by a reviewer to assess their relevance against the predefined eligibility criteria. Articles that met these criteria were then subjected to a full-text evaluation. To ensure transparency, the entire study selection process was documented using a PRISMA flow diagram.

2.4. Data Extraction

A data extraction form was developed based on previous investigations. The extracted data included article identifiers such as authors and year, a summary of the development or intervention, the results and conclusions as reported by the authors, and an assessment of the risk of bias in the study reporting.

2.5. Quality Assessment

In evaluating the quality of the included studies, we focused on a critical and specific aspect: the assessment of reporting bias risk. It is noteworthy that we chose to employ established quality assessment tools to adhere to the customary reporting standards for systematic reviews.

To gauge the risk of reporting bias, we employed a visual RAG (red, amber, green) ranking system, a tool previously utilized by Gordon et al. [10], and Stojan et al. [11]. The assessed areas encompassed foundational theories, available resources, educational settings, pedagogical methods, and subject matter (Table 2). Items were categorized as exhibiting a low risk of bias (green), a moderate risk of bias (amber), or a high risk of bias (red).

Table 2. Quality assessment/risk of bias of the interventions presented [11].

Bias Source	Low Risk	Moderate Risk	High Risk
Underpinning bias (U)	A clear and relevant description of the theoretical models or conceptual frameworks that underpin development	A limited discussion of underpinning, with minimal interpretation in the context of the study	No mention of underpinning
Resource bias (R)	A clear description of the cost/time/resources needed for development	A limited description of resources	No mention of resources
Setting bias (S)	Clear details of the educational context and learner characteristics of the study	Some description, but not significant enough to support dissemination	No details of learner characteristics or setting
Educational bias (E)	A clear description of relevant educational methods employed to support delivery	Some educational methods mentioned but limited detail as to how they are applied	No details of educational methods
Content bias (C)	The provision of detailed materials (or details of access)	Some elements of materials presented or summary information	No educational content presented

2.6. Data Synthesis

Given the anticipated diversity in study designs, AI applications, and personalized learning approaches, a narrative synthesis approach was adopted to provide a structured and comprehensive analysis. Thematic analysis was conducted to identify key trends related to AI-driven personalized learning strategies, focusing on aspects such as adaptive learning algorithms, student engagement, and pedagogical effectiveness. Data analysis was performed using NVivo version 12, with a predefined coding framework emphasizing critical elements such as AI-based recommendation systems, intelligent tutoring, and real-time learning analytics. This process enabled the systematic identification of common themes and their impact on personalized learning experiences in higher education. Additionally, descriptive statistics were employed to summarize the study characteristics and key findings, which are presented through tables and figures. The data synthesis aimed to provide a thorough overview of the current research landscape, highlight best practices, and identify gaps requiring further investigation.

2.7. Ethical Considerations

As this study exclusively analyzed publicly available data, formal ethical approval was not required. However, ethical principles were rigorously upheld throughout the research process. This included ensuring transparency in data selection, accuracy in reporting the findings, and respect for intellectual property rights. Additionally, considerations regarding the ethical implications of AI in education—such as student data privacy, algorithmic bias, and academic integrity—were acknowledged to reflect the broader ethical challenges associated with AI-driven personalized learning.

3. Results

This section presents the findings from the literature review, including a PRISMA flow diagram, a comprehensive table summarizing the 45 included studies, and an analysis of the extracted data.

3.1. Study Selection Results

The study selection process adhered to the PRISMA guidelines [6]. The initial database search yielded 17,899 articles. After removing duplicates and applying the inclusion and exclusion criteria, eight studies were deemed eligible for inclusion in this review. A PRISMA flow diagram illustrating this process is presented in Figure 1.

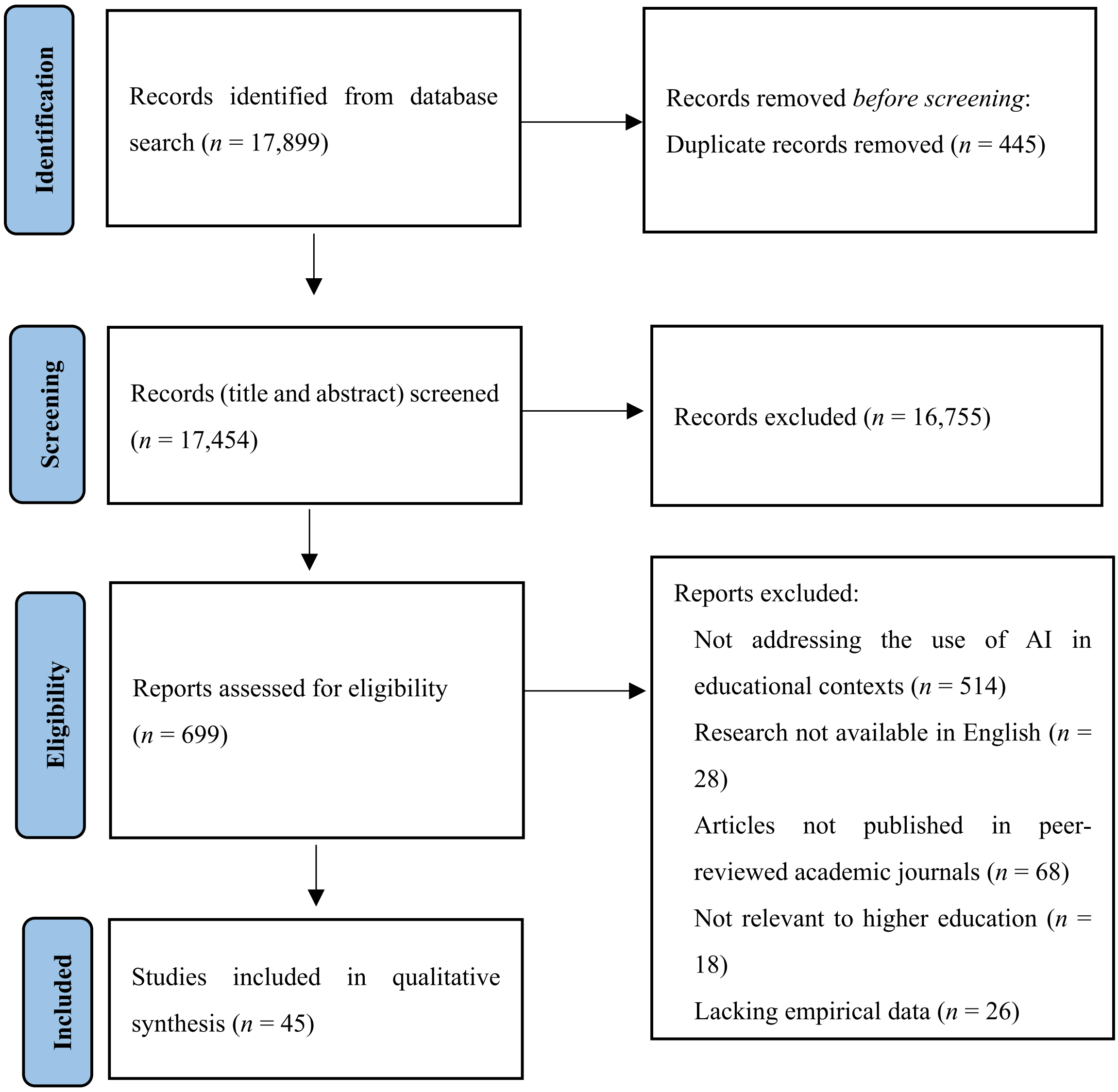

Figure 1. PRISMA Flow Diagram.

The initial search identified 17,899 records. After removing duplicates, 17454 remained for screening. Of these, 699 underwent full-text review, with 654 excluded for reasons including a lack of empirical data, a non-higher-education focus, and methodological weaknesses. The final review included 45 studies.

3.2. Characteristics of Included Studies

The 45 studies included in this review explored various applications of AI in personalized learning in higher education. The characteristics of the included studies are summarized in Table 3.

Table 3. Included studies.

Authors and Year	Intervention/Development Summary	Results and Conclusions	Risk of Bias in Study Reporting				
			U	R	S	E	C
Abulibdeh et al. (2024). [12]	Review of ethical and practical dimensions of AI integration in education.	Concludes that AI improves learning efficiency but raises ethical and infrastructural challenges.					
Al-Zahrani & Alasmari (2024). [13]	Investigates ethical, social, and pedagogical implications of AI in education.	Identifies significant benefits alongside concerns over academic integrity and bias.					
Amin et al. (2023). [14]	Describes the development of a recommended system for e-learning based on IoT and AI.	Demonstrates potential for personalized content delivery and improved course selection.					
Azevedo et al. (2024). [15]	Provides a dataset supporting personalized learning and assessment analytics.	Highlights the potential for data-driven personalization in higher education.					
Bognar et al. (2024). [16]	Empirical investigation comparing classical theories with AI-enhanced learning.	Finds that AI can boost engagement if classical components are adequately integrated.					
Bukar et al. (2024). [17]	Uses an analytical approach to assess ethical challenges of ChatGPT use.	Concludes that ethical concerns must be balanced with pedagogical benefits.					
Chan & Hu (2023). [18]	Qualitative study exploring student perceptions of generative AI.	Reports predominantly positive perceptions with some ethical concerns.					
Chan & Lee (2023). [19]	Compares generational attitudes toward generative AI in educational contexts.	Finds significant enthusiasm among Gen Z compared to older generations.					
Demartini et al. (2024). [20]	Presents a study on AI-empowered adaptive learning modules.	Demonstrates improved learning outcomes when instructors support AI integration.					
Eltahir & Babiker (2024). [21]	Study assessing the impact of AI tools on e-learning performance.	Shows that AI-enhanced environments can improve student performance.					
Gallent-Torres et al. (2023). [22]	Explores the ethical implications of using generative AI in academic settings.	Highlights potential benefits alongside serious concerns regarding academic integrity.					
George & Wooden (2023). [23]	Study on strategic management of AI integration in higher education.	Finds that AI can streamline administration and support institutional transformation.					
Gouia-Zarrad & Gunn (2024). [24]	Evaluates ChatGPT as a tool to support mathematics learning.	Reports improved engagement and understanding, with some limitations noted.					
Grosseck et al. (2024). [25]	Survey study of digital assessment practices and needs among university teachers.	Indicates that digital tools can enhance assessment, though teacher training is needed.					
Hang et al. (2024). [26]	Describes a tool for generating multiple-choice questions using LLMs for personalized learning.	Demonstrates efficiency in MCQ creation, supporting tailored assessments.					

Table 3. *Cont.*

Authors and Year	Intervention/Development Summary	Results and Conclusions	Risk of Bias in Study Reporting				
			U	R	S	E	C
Hooshyar et al. (2023). [27]	Explores methods to combine neural networks with symbolic knowledge for interpretable AI in education.	Concludes that hybrid models can enhance trustworthiness and interpretability.					
Hooshyar et al. (2024). [28]	Proposes a predictive model for student performance in educational gaming environments.	Demonstrates promising predictive accuracy for early intervention.					
Huang (2024). [29]	Describes an AI-based approach for enhancing English learning in blended environments.	Reports improvements in language proficiency and engagement.					
Ilic et al. (2023). [30]	Literature review on the application of intelligent techniques in e-learning.	Summarizes diverse methods and stresses the need for further empirical validation.					
Ilieva et al. (2023). [31]	Investigates the effects of generative chatbots on student learning experiences.	Finds that chatbots increase engagement but require careful integration to avoid superficial learning.					
Kamalov et al. (2023). [32]	Proposes a theoretical framework for sustainable AI integration in education.	Emphasizes innovation potential alongside challenges in resource allocation.					
Kamruzzaman et al. (2023). [33]	Discusses the integration of AI and IoT to support sustainable education during pandemics.	Shows that technology can ensure continuity and efficiency in education during crises.					
Kiryakova & Angelova (2023). [34]	Qualitative study on the challenges of integrating ChatGPT in teaching practices.	Reveals mixed perceptions: potential benefits are recognized, but concerns about academic integrity persist.					
Lewandrowski et al. (2023). [35]	Extensive series evaluating the impact of technology-driven interventions in postgraduate settings.	Demonstrates that technology-driven interventions can have a positive impact, though some aspects require improvement.					
Ma et al. (2023). [36]	Proposes a multi-algorithm framework for recommending personalized learning paths.	Demonstrates improved student learning outcomes through adaptive recommendations.					
Madsen et al. (2024). [37]	Explores the use of ChatGPT as a tool for fostering self-directed learning in medical education.	Indicates that ChatGPT can enhance learning if integrated with proper guidance.					
Naseer et al. (2024). [38]	Evaluates deep learning techniques to generate personalized learning pathways.	Reports significant improvements in student engagement and performance.					
Neumann et al. (2025). [39]	Develops an LLM-based chatbot to assist with database course material and queries.	Demonstrates high accuracy and usefulness in supporting student learning.					

Table 3. *Cont.*

Authors and Year	Intervention/Development Summary	Results and Conclusions	Risk of Bias in Study Reporting				
			U	R	S	E	C
Ogata et al. (2024). [40]	Presents an explainable AI tool for generating personalized educational content.	Concludes that enhanced explainability increases teacher and student trust in AI systems.					
Pham et al. (2023). [41]	Examines the impact of AI-assisted learning tools in engineering education.	Reports increased student engagement and efficiency in learning complex engineering concepts.					
Rahiman & Kodikal (2024). [42]	Describes the development and application of AI-empowered learning modules.	Indicates enhanced academic performance when AI is effectively integrated.					
Sailer et al. (2024). [43]	Proposes a closed-loop framework for learning analytics to support personalized feedback.	Demonstrates potential for iterative improvements in student learning through analytics.					
Sajja et al. (2024). [44]	Develops an intelligent assistant using AI to provide personalized, adaptive learning support.	Shows improved student engagement and tailored learning experiences.					
Saleem et al. (2024). [45]	Evaluates the use of ChatGPT as a self-directed learning tool in medical education.	Concludes that ChatGPT can foster independent learning when integrated with proper oversight.					
Sallam & Al-Salahat (2023). [46]	Compares ChatGPT's exam performance with that of university students in medical microbiology.	Finds that ChatGPT's performance is inferior, suggesting limitations in its academic reliability.					
Shabbir et al. (2024). [47]	Explores ChatGPT's potential to enhance educational access and engagement in resource-limited settings.	Highlights both transformative potential and challenges such as academic integrity.					
Shimizu et al. (2023). [48]	Qualitative study on curriculum reform strategies in response to generative AI's impacts in medical education.	Suggests that curriculum reforms are necessary to accommodate the rapid adoption of AI tools in education.					
Wang & Li (2024). [49]	Examines the influence of AI tools on students' willingness to engage in autonomous learning.	Concludes that effective AI integration can foster independent learning behaviors.					
Wang et al. (2023). [50]	Explores various AI applications (e.g., chatbots, adaptive systems) for supporting international students' success.	Indicates that personalized AI interventions can improve academic performance while raising privacy and cultural concerns.					
Weber et al. (2024). [51]	Investigates the impact of formative feedback delivered in a hybrid AI-enhanced environment.	Reports that structured feedback significantly improves legal writing skills.					

Table 3. *Cont.*

Authors and Year	Intervention/Development Summary	Results and Conclusions	Risk of Bias in Study Reporting				
			U	R	S	E	C
Xu et al. (2024a). [52]	Reviews current applications and challenges of ChatGPT in medical education.	Identifies both potential for enhanced learning and challenges, including ethical concerns.	Green	Red	Green	Green	Green
Xu et al. (2024b). [53]	Interviews experts on the impact of ChatGPT in mitigating the side effects of personal learning environments.	Suggests that expert guidance is needed to optimize ChatGPT integration in higher education.	Green	Amber	Green	Green	Green
Yefymenko et al. (2024). [54]	Explores interactive AI tools for teaching foreign languages and translation.	Indicates that AI tools enhance language instruction while addressing translation challenges.	Green	Green	Green	Green	Green
Yigci et al. (2024). [55]	Reviews the use of LLM-based chatbots to support personalized learning in higher education.	Concludes that chatbots offer significant benefits in terms of scalability and personalized support despite some limitations.	Green	Green	Green	Green	Amber
Yoo et al. (2023). [56]	Develops a model using LSTM networks to predict cognitive load during learning tasks.	Demonstrates promising predictive performance to support adaptive learning interventions.	Green	Green	Green	Green	Green

Note: Colors indicate the level of risk of bias: green represents low risk, amber represents moderate risk, and red represents high risk. C = Content bias; E = Educational bias; R = Resource bias; S = Setting bias; U = Underpinning bias.

3.3. Result Analysis

The results of this review indicate that AI-based recommendation systems play a significant role in adapting learning materials to individual students, enhancing engagement and knowledge retention [14,36]. Intelligent tutoring systems, leveraging adaptive feedback, have shown measurable improvements in student performance [20,26]. Furthermore, real-time learning analytics enable educators to identify at-risk students early, allowing timely pedagogical interventions [44]. These findings underscore the transformative potential of AI across multiple dimensions of personalized learning.

AI technologies, such as intelligent tutoring systems, adaptive learning platforms, and machine learning algorithms, significantly improved learning outcomes. Students using AI tools, reported higher engagement, better test scores, and increased motivation.

Within higher education, studies demonstrate that AI can enhance academic performance and engagement by offering tailored learning experiences. For instance, adaptive AI systems implemented in university courses have shown improvements in both student motivation and course completion rates, underscoring the transformative potential of these technologies in higher-education environments.

The challenges included ethical concerns (e.g., data privacy, algorithmic bias), limited teacher training in AI tools, and infrastructural limitations in some educational contexts.

Specifically, in higher education, data security concerns are exacerbated by the vast datasets collected for analytics. Universities must ensure compliance with privacy regulations while fostering trust among students and educators regarding data use. Additionally, faculty members often require targeted training to integrate AI tools into their teaching practices, an area that remains underdeveloped

Studies emphasized the scalability of AI-powered solutions to diverse educational environments. However, their successful implementation depends on contextual adaptation and stakeholder collaboration.

The risk of bias in these studies is visually presented in Figure 2 and detailed in Table 3. Generally, the studies exhibited a low risk of bias, with their quality generally rated from moderate to high. This may be attributed to the length of the articles and the impact factors of the journals in which they were published.

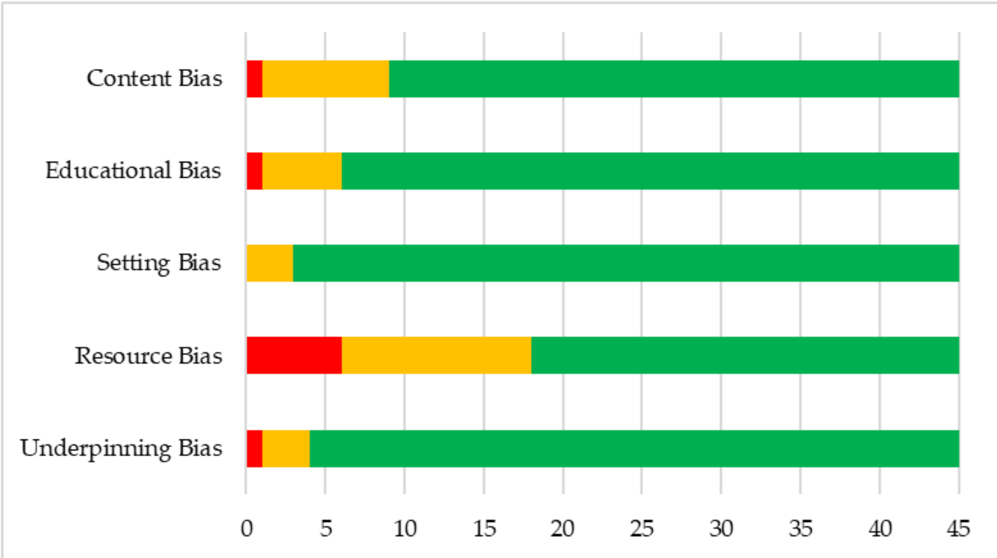

Figure 2. Risk of bias in study reporting. Colors indicate the level of risk of bias: green represents low risk, amber represents moderate risk, and red represents high risk.

4. Discussion

This review synthesized a diverse body of research on the impact of AI in fostering personalized learning within a higher-education context. The discussion below elaborates on the main findings, their implications for theory and practice, limitations inherent in the current literature, and avenues for future research, while consistently integrating key references from the included studies.

The evidence across 45 studies confirms that AI-driven solutions can play a transformative role in higher education by enabling personalized learning experiences. For instance, Abulibdeh et al. [12] provided a comprehensive review of the ethical and practical dimensions of AI integration in higher-education institutions across multiple countries, demonstrating that AI can improve learning efficiency, albeit with significant ethical and infrastructural challenges. Similarly, Amin et al. [14] introduced a recommended system for e-learning that leverages IoT and AI to offer personalized content delivery, suggesting that technical innovations can directly enhance student course selection and learning experiences.

Furthermore, Azevedo et al. [15] and Kiryakova and Angelova [34] highlighted the potential of data-driven personalization and adaptive learning technologies. Their systematic approaches underscore that when AI is tailored to individual learning styles, it can significantly improve academic outcomes. Demartini et al. [20] and Chan and Hu [19] add to this evidence by showing that adaptive learning modules and student perceptions of generative AI, respectively, offer promising enhancements in engagement and performance. However, these benefits are not without challenges. Gallent-Torres et al. [22] and Bukar et al. [17] reveal that concerns regarding academic integrity, data privacy, and algorithmic bias persist, suggesting that the integration of AI in educational settings must be approached with careful consideration of its ethical implications.

The body of literature reviewed confirms that AI-driven solutions have the potential to transform personalized learning in higher education by improving engagement, efficiency, and academic performance. Nevertheless, the integration of these technologies presents significant challenges that must be addressed. Future research should emphasize robust, standardized, and context-sensitive approaches to fully harness the transformative potential of AI in higher education. This balanced approach will ensure that AI innovations contribute to a more adaptive, equitable, and effective learning environment for all stakeholders.

These findings emphasize the necessity for higher-education institutions to establish clear AI implementation guidelines. Educators should receive targeted training to leverage AI responsibly while mitigating ethical concerns. Policymakers must ensure regulatory frameworks that balance technological advancements with academic integrity and equity considerations.

4.1. Pedagogical Transformation

The reviewed studies suggest that AI not only enhances content delivery but also drives a fundamental transformation in pedagogical practices. Chan and Lee [19] found that generational differences play a critical role in the adoption of AI tools, with Gen Z students exhibiting higher enthusiasm for such innovations compared to older educators. This points to the need for modern curricula that incorporate digital interactivity as a core component of learning. Additionally, adaptive systems, as described by Hooshyar et al. [28] and Ma et al. [36], enable instructors to tailor educational materials to the diverse needs of students, thereby fostering a more inclusive environment that can address individual learning gaps.

4.2. Institutional and Administrative Innovation

AI's implications extend beyond the classroom into institutional and administrative domains. George and Wooden [23] presented a case study demonstrating that strategic AI integration can streamline administrative processes such as scheduling and resource allocation, thus enhancing overall institutional efficiency. Similarly, Kamalov et al. [32] propose a sustainable framework for AI adoption that balances innovation with resource constraints, a critical factor for university administrators. The work by Neumann et al. [38] further illustrates that AI-powered chatbots can effectively support academic tasks, reinforcing the idea that technology can be a vital tool for institutional transformation.

4.3. Ethical and Regulatory Considerations

A recurring theme in the literature is the ethical dimension of AI integration. Al-Zahrani and Alasmari [13] underscore the need to address concerns regarding academic integrity and bias. Bukar et al. [17] and Ilieva et al. [31] also caution that without proper regulation, the benefits of AI might be undermined by data privacy issues and algorithmic biases. These ethical concerns demand robust policy frameworks. For example, the studies by Shabbir et al. [47] and Kamruzzaman et al. [33] indicate that while AI-driven interventions can enhance learning in underdeveloped regions or during crises, they must be paired with strong ethical guidelines and data governance protocols to ensure fair and responsible use.

Ethical concerns in AI-driven education extend beyond data privacy to encompass disparities in access to AI technologies. Institutions in resource-limited settings may struggle to implement AI solutions, exacerbating existing educational inequalities [47]. Additionally, there is growing apprehension regarding the impact of AI on teacher autonomy [13]. While

AI-powered tools can enhance personalized learning, they may also lead to over-reliance on algorithm-driven decisions, potentially diminishing educators' role in curriculum design and student engagement.

4.4. Limitations

Despite their promising findings, several limitations were noted across the reviewed studies.

Although several articles provided strong theoretical underpinnings [15,29], others showed moderate risk in areas such as resource description and contextual details [12,48]. This heterogeneity in quality calls for more standardized reporting protocols in future studies.

A few studies [13,49,52] highlight persistent ethical challenges. These include concerns about academic integrity, data privacy, and algorithmic bias, which are not always fully addressed in the current literature.

A key limitation observed in the reviewed studies is the variability in methodological rigor, particularly regarding sample representativeness and data validation processes. Several studies relied heavily on self-reported data, which may introduce biases that affect the reliability of their conclusions [28,30,51]. Furthermore, the generalizability of the findings is limited due to the predominance of studies conducted in technologically advanced regions, potentially overlooking challenges faced in underrepresented areas [22,35].

4.5. Future Research

To strengthen the evidence base, future research should employ longitudinal and experimental designs. Neumann et al. [38] demonstrated the utility of LLM-based chatbots in a cross-sectional study; however, randomized controlled trials and long-term evaluations are necessary to establish causality and assess the sustainability of AI-driven interventions.

The current heterogeneity in methodologies underscores the need for standardized evaluation metrics. Future studies should aim to develop common frameworks to assess student engagement, learning efficiency, and ethical compliance. Such standardization would enable more robust meta-analyses and facilitate comparisons across different educational contexts [37,54].

Research must further investigate the ethical dimensions of AI in education. For instance, studies by Kamruzzaman et al. [33] and Shabbir et al. [47] call for comprehensive ethical guidelines to mitigate risks related to data privacy and bias. Collaborative research involving educators, policymakers, and technologists is essential to develop frameworks that ensure responsible AI integration while maximizing its benefits.

Future research should also focus on context-specific studies, particularly in underrepresented regions and among diverse student populations. Shabbir et al. [47] provide valuable insights into AI applications in underdeveloped regions; however, further research is needed to explore how cultural, economic, and institutional factors influence the effectiveness of AI-driven personalized learning. Comparative studies across different countries and educational systems would contribute significantly to understanding these contextual nuances.

Future research should prioritize longitudinal studies to assess the long-term effectiveness of AI-driven learning interventions [38,43]. Additionally, comparative studies across diverse educational contexts—such as developing versus developed nations—could provide valuable insights into the scalability of AI applications [48,50]. Mixed-methods approaches, combining quantitative analytics with qualitative feedback from educators and students, are recommended to ensure a holistic understanding of AI's impact on learning outcomes.

5. Conclusions

This review demonstrates that AI-driven solutions hold considerable potential to enhance personalized learning within higher education. The evidence indicates that AI applications can improve learning efficiency, tailor educational content, and streamline administrative processes, offering opportunities to boost student engagement and performance. At the same time, these technologies present challenges, including ethical concerns, data privacy issues, and the need for effective teacher training and support.

However, the current body of literature is marked by methodological variability and inconsistent reporting, highlighting the need for standardized evaluation frameworks and more robust, longitudinal research designs. Future studies should focus on establishing causal relationships, assessing long-term sustainability, and developing standardized metrics for measuring outcomes such as engagement, academic performance, and ethical compliance.

Ultimately, while the transformative potential of AI in personalized learning is evident, fully realizing its benefits requires a balanced approach that addresses both its opportunities and limitations. As higher-education institutions continue to integrate AI technologies, it is essential for educators, policymakers, and administrators to collaborate in developing ethical, scalable, and context-sensitive implementations that enhance the overall learning environment.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
C	Content bias
E	Educational bias
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
R	Resource bias
RAG	Red, amber, green
S	Setting bias
U	Underpinning bias

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