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Leveraging AI-Driven Personalized Learning Tools to Bridge Educational Inequities in STEM Education: A Path Toward Just and Inclusive Learning Environments

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Abstract
This study explores the role of artificial intelligence (AI) in creating equitable learning opportunities within STEM education. By employing a systematic literature review, bibliometric analysis, and conducted a survey of 150 educators across diverse educational institutions, the research examines the effectiveness of AI-driven personalized learning tools in addressing educational disparities. The findings from the survey reveal that AI tools are more commonly used in private schools, where resources are more abundant, compared to public schools, where limited access to technology remains a barrier. The study demonstrates that AI-driven personalized learning can significantly enhance academic outcomes and student engagement in STEM fields by providing tailored instructional support that meets individual learning needs. However, the research also highlights potential challenges, including the risk of reinforcing existing biases and the digital divide, which could undermine efforts to achieve educational equity. The study concludes that while AI has the potential to democratize STEM education, its successful implementation requires careful attention to ethical considerations and equitable access to technology. The implications of this research are critical for educators, policymakers, and technology developers, providing insights into how AI can be effectively utilized to create more just and inclusive STEM learning environments.

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1. Introduction

With the advancement in technology, artificial intelligence is transforming the field of education and also creating impact on students' performance enrolled in middle school STEM education. AI has the capability to transform the old teaching and learning methods, and has a role in improving the manner of doing research. In domain of higher education, AI has a major part in revolutionizing learning and pedagogical principles (Kenchakkanavar, 2023) [17]. AI enhances the chances of students learning and make the acquisition of knowledge better by introducing personalized learning, analytics, and instructional automation (Triplett, 2023) [35]. Artificial Intelligence (AI) enhances student learning and performance by providing personalized, simulation-based, and interactive tools in education. It supports both teaching and administration, especially benefiting special needs students through customized instructions. While AI complements human teachers, its role is vital in delivering effective education across diverse environments (Kanyike, 2024). Even though artificial intelligence (AI) has the potential to revolutionize education, resolving the enduring educational disparities that impact underprivileged and marginalized student populations is still very difficult (Ayanwale *et al*., 2024). A number of variables, including socioeconomic position, resource accessibility, and institutionalized biases in the educational system, frequently make these disparities worse (Doyle *et al*., 2022) [6].

2. Problem Statement

While AI-driven personalized learning tools have shown promise in enhancing learning outcomes, their impact on reducing educational inequities in STEM education remains underexplored (Wang *et al*., 2024) [37]. There is a critical need to investigate how these tools can be leveraged to bridge the gap between students from diverse backgrounds, ensuring that all students, regardless of their circumstances, have equal opportunities to succeed in STEM disciplines. Without a deliberate focus on equity, the widespread adoption of AI in education risks perpetuating or even widening existing disparities (Pesovski *et al*., 2024) [27].

The study aimed to evaluate the potential of AI-driven personalized learning tools in addressing and reducing educational inequities in STEM education, with a focus on creating more just and inclusive learning environments for students from diverse socioeconomic backgrounds.

Specific Objectives of the study are:

- **Effectiveness of AI in Education:** to assess the impact of AI-driven personalized learning systems on academic performance, student engagement, and overall satisfaction within STEM education;
- **Equity and Bias Mitigation:** to explore the role of AI tools in addressing and mitigating biases related to socioeconomic status, race, and access to technology in educational settings;
- **Inclusivity in STEM Education:** to examine how AI-driven personalized learning can be leveraged to create more equitable opportunities in STEM education for marginalized and underrepresented student groups;
- **Educational Outcomes and Equity:** to investigate the long-term effects of AI integration in STEM education on bridging the achievement gap between students from diverse backgrounds.

In order to ensure objectivity and facilitate data curation and analysis, a Systematic Literature Review (SLR) was conducted to answer the following research questions:

- **Effectiveness of AI in Education:** How effective are AI-driven personalized learning tools in improving academic achievement, student engagement, and satisfaction in STEM education?
- **Equity and Bias Mitigation:** To what extent can AI-driven personalized learning systems reduce biases related to socioeconomic status, race, and access to technology in STEM education?
- **Inclusivity in STEM Education:** How can AI-driven personalized learning tools be utilized to provide equitable opportunities in STEM education for marginalized and underrepresented student groups?
- **Educational Outcomes and Equity:** What are the long-term effects of integrating AI-driven personalized learning tools on reducing educational disparities and bridging the achievement gap in STEM education among students from diverse socioeconomic backgrounds?

3. Theoretical Framework

The theoretical framework for the study is grounded in several interconnected theories that address educational equity, technology in education, and the role of artificial intelligence (AI) in personalized learning.

a) **Critical pedagogy:** rooted in the work of Paulo Freire, critical pedagogy emphasizes the role of education in challenging societal inequalities and empowering marginalized communities (Freire, 1996; Panthi, 2023) [8, 26]. Several teachers use critical strategies such as dialogical methods, connecting learning with real-life situations, engaging students in out-of-book activities, and employing problem-solving techniques to positively impact student thinking and learning. These methods encourage students to engage actively in their learning, fostering critical thinking skills and enhancing their ability to connect classroom knowledge to real-world contexts (Skelton, 2023) [33]. This framework guided the exploration of how AI-driven personalized learning tools can be used to democratize education, particularly in STEM (Science, Technology, Engineering, and Mathematics) fields. The study investigated whether these tools help bridge gaps for marginalized students by providing equitable learning opportunities and fostering critical engagement with STEM content.

b) **Equity Theory:** equity theory, originating from social psychology, posits that individuals seek fairness in their interactions and outcomes. In education, equity theory is applied to ensure that all students, regardless of their background, have access to the same opportunities and resources to succeed (Levinson *et al*., 2022) [23]. The study leveraged equity theory to assess the effectiveness of AI-driven personalized learning tools in leveling the playing field for students from different socioeconomic statuses, racial backgrounds, and other marginalized groups in STEM education. It evaluated whether these tools provided tailored support that met the unique needs of each student, thereby promoting fairness and justice in educational outcomes (Roshanaei *et al*., 2023) [29].

c) **Cultural-Historical Activity Theory (CHAT):** CHAT, developed by Vygotsky and later expanded by Engeström, focuses on how social, cultural, and historical contexts influence learning and development. It emphasizes the role of tools (including technology) in mediating learning and the importance of community and collaborative practices in educational settings (Yamagata-Lynch, 2010) [39]. CHAT was used to understand how AI-driven personalized learning tools were integrated into the educational ecosystem, particularly in STEAM subjects. The study examined how these tools interacted with the cultural and historical contexts of learners and how they could be designed to support collaborative and inclusive learning environments.

d) **Personalized learning theory:** this theory centers on the idea that educational experiences should be tailored to the individual needs, preferences, and strengths of each student. It emphasizes adaptive learning environments where technology plays a crucial role in providing customized educational experiences (Gunawardena *et* *al*., 2024) [9]. This theory underpinned the investigation of how AI-driven personalized learning tools could customize STEM education to fit the diverse learning styles and needs of students. The study explored the extent to which these tools could enhance engagement and learning outcomes by providing individualized support and feedback (Shemshack & Spector, 2020) [31].

e) **Technological Pedagogical Content Knowledge (TPACK):** TPACK is a framework that identifies the knowledge teachers need to effectively integrate technology into their teaching. It highlights the intersection of technology, pedagogy, and content knowledge, emphasizing that effective teaching with technology requires an understanding of how these three areas interact (Sierra *et al*., 2023) [32]. The study utilized the TPACK framework to analyze how teachers could effectively incorporate AI-driven personalized learning tools into their STEAM classrooms. It examined the pedagogical strategies and content knowledge required to maximize the benefits of these tools and ensure they were used to promote equity and inclusion.

4. Research hypotheses

The study is based on a number of assumptions:

- AI-driven personalized learning tools significantly improve academic achievement, student engagement, and satisfaction in STEM education compared to traditional teaching methods.
- AI-driven personalized learning systems reduce biases related to socioeconomic status, race, and access to technology in STEM education, leading to more equitable educational outcomes.
- AI-driven personalized learning tools provide more equitable opportunities for marginalized and underrepresented student groups in STEM education, resulting in improved educational outcomes for these populations.
- The integration of AI-driven personalized learning tools in STEM education leads to a significant reduction in educational disparities and contributes to bridging the achievement gap among students from diverse socioeconomic backgrounds over time.

5. Methodology

5.1 Formulation of key concepts, relationship analysis and supporting Ideas

The conceptual framework development involved refining AI-related concepts through literature review and concept mapping, which organized ideas and explored relationships among key concepts like administrative task reduction, instructional efficiency, and student outcomes. This process helped create research questions and identify keywords for a systematic review, ensuring a thorough exploration of the topic.

5.2 Data Extraction/Qualitative Synthesis

A rigorous data extraction process was implemented using a systematic literature review with bibliometric analysis (SLRBA) to ensure the reliability and consistency of the information gathered. The process involved systematically reviewing and coding relevant details from selected academic publications, focusing on the application and impact of AI-driven personalized learning tools in education. The primary goal was to capture a comprehensive view of how these tools influence educational equity, particularly in STEM (Science, Technology, Engineering, and Mathematics) education (Donthu *et al*., 2021; Rosário *et al*., 2021) [5, 28].

5.3 Data sources and search strategy

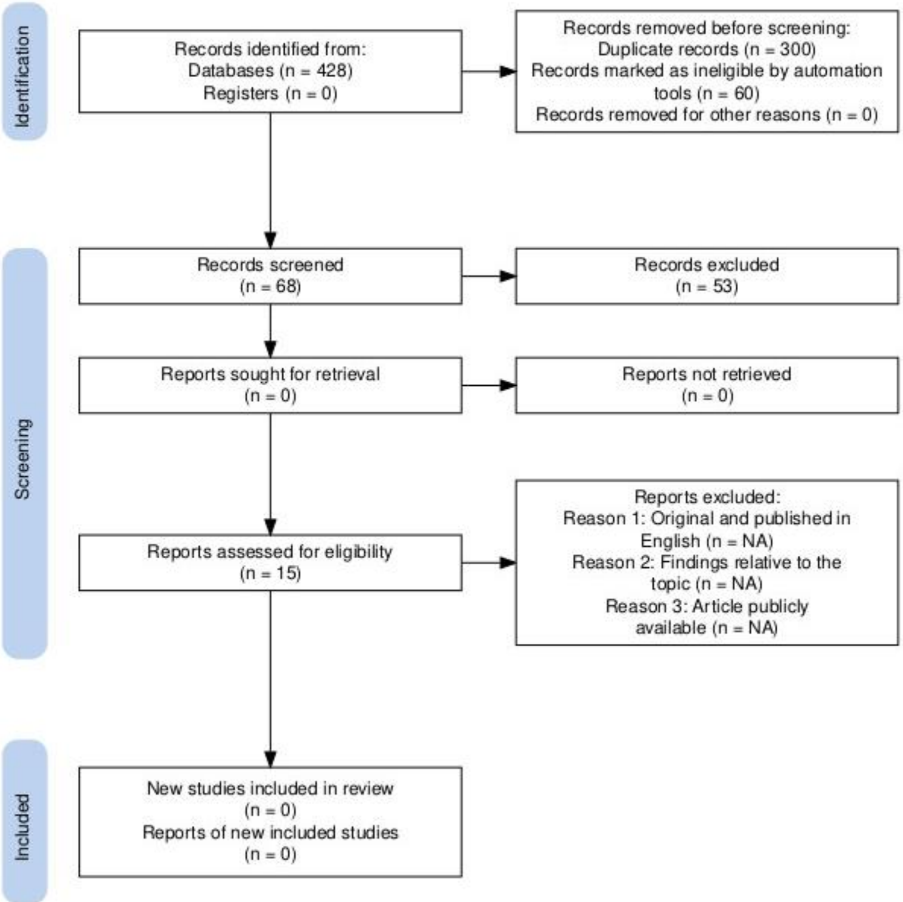
To evaluate the impact of AI on reducing administrative burden and enhancing instructional efficiency in middle schools, a systematic review following PRISMA criteria was conducted using databases like Google Scholar, PubMed, Scopus, Web of Science, JSTOR, and ProQuest. Relevant articles from 2019 to 2024 were identified using keywords combined with Boolean terms "OR" and "AND." The study documented original research and recent studies on the impact of AI-driven personalized learning tools in bridging educational inequities in STEM education, highlighting their role in creating more just and inclusive learning environments.

5.4 Selection Criteria

Inclusion criteria for the qualitative synthesis required articles to be original, published in English, and from journals or conference proceedings. Theses and dissertations were excluded. Selected documents focused on the impact of AI-driven personalized learning tools in bridging educational inequities in STEM education, emphasizing their role in fostering just and inclusive learning environments.

5.5 Article selection process

Initially, 428 records were identified from various databases and screened for title and keyword relevance. After removing 300 duplicates and 60 ineligible records using automation tools, 68 articles were retained. These articles were further screened by reading abstracts for relevant information. Final screening based on predefined inclusion criteria excluded articles not meeting all criteria. This stepwise selection process resulted in 15 articles being chosen for qualitative synthesis, as shown in Figure 1.



Source: Haddaway *et al*. (2020) [10]

Fig 1: Identification of new studies via databases and registers (PRISMA diagram)

5.6 Data Extraction/Qualitative Synthesis

A standardized data extraction procedure was followed to minimize subjectivity, involving the capture and coding of relevant information from selected articles. The synthesized information was used to address the research questions. An Excel sheet was prepared to record, code, and synthesize data, including author names, publication titles, journal names, publication years, research questions and aims, conceptual frameworks, research designs, methods and data analysis, key findings, and limitations and future research. This enabled comprehensive data extraction for analysis.

5.7 Data analysis

The data analysis employed a systematic, mixed-methods approach, integrating both quantitative and qualitative analyses to comprehensively address the research objectives. Additionally, survey data was utilized to gather demographic information about STEM education.

a) Quantitative Analysis

- **Regression Analysis:** To test the hypothesis that AI-driven personalized learning systems significantly improve academic achievement, learner engagement, and satisfaction, regression models were developed. These models analyzed student performance and engagement metrics before and after implementing AI tools in various educational settings.
- **Equity Impact Assessment:** The hypothesis that AI tools could either exacerbate or mitigate educational biases was tested using equity metrics. These metrics quantified disparities in outcomes based on socioeconomic status (SES), race, and other demographic factors, offering insights into AI's effectiveness in reducing educational inequities.
- **Co-occurrence Analysis:** Bibliometric methods, including co-occurrence analysis, mapped relationships between key concepts such as AI, personalized learning, equity, and STEAM education. This analysis identified research trends and gaps that the study aimed to address.

b) Qualitative Analysis

- **Thematic Analysis:** Qualitative data from study findings, including teacher and student feedback on AI tools, were subjected to thematic analysis. This process identified recurring themes related to the benefits and challenges of using AI in personalized learning and its impact on educational equity.
- **Content Analysis:** A content analysis was conducted on the limitations and future research sections of the reviewed studies to uncover patterns in identified challenges and propose directions for future research to address these gaps.

c) Integration of Quantitative and Qualitative Data: The mixed-methods approach facilitated the integration of quantitative and qualitative findings, ensuring a comprehensive analysis of the research questions. The combination of statistical data, thematic insights, and demographic information from survey results provided a nuanced understanding of how AI-driven personalized learning tools impact STEM education and whether these tools contribute to more equitable learning environments.

d) **Ethical Considerations:** Throughout the study, ethical considerations were meticulously observed. Data privacy was safeguarded by anonymizing personal information, and all sources were credited in compliance with copyright laws (Ducato, 2020; Hornuf *et al*., 2023) [7, 13]. The research also adhered to ethical guidelines for the use of AI in education, ensuring that the potential biases and risks associated with AI tools were critically assessed.

6. Results

6.1 Classification of articles by journal

The Table 1 categorizes articles by their respective journals or publishers, offering insights into the diversity and focus areas of research on AI-driven personalized learning and educational equity. The broad range of journals reflects the interdisciplinary nature of this research, spanning education, technology, and psychology. Notably, Teaching and Teacher Education is the most represented journal, emphasizing the role of educators in implementing AI-driven tools. Other significant journals, like the British Journal of Educational Psychology and the British Journal of Educational Technology, further highlight the psychological and technological aspects of AI in education. The inclusion of prominent journals such as Expert Systems With Applications, Sustainability, and BMJ underscores the broader impact of AI, including its application in sustainable practices and the intersection of education, health, and technology. The presence of journals like Philosophy & Technology and AERA Open indicates an engagement with ethical, philosophical, and open-access research, reinforcing the comprehensive approach needed to address educational disparities through AI. Overall, the table highlights the complexity of AI research in education and the importance of interdisciplinary approaches in fostering educational equity (Table 1).

Table 1: A Comprehensive Review of AI-Driven Personalized Learning Tools: Diverse Perspectives from Reputable Journals

Authors and year	Journal or Publisher
Wang *et al*. (2024)	Expert Systems With Applications
Das *et al*. (2017)	International Journal of Computer Sciences and Engineering
Doyle *et al*. (2022)	British Journal of Educational Psychology
(Molla & Gale, 2023)	Journal of Education Policy
Allotey *et al*. (2023)	Humanities and Social Sciences Communications
Juhn *et al*. (2024)	In Elsevier eBooks
Leslie *et al*. (2021)	BMJ
Bulathwela *et al*. (2024)	Sustainability
Shanklin *et al*. (2022)	Philosophy & Technology
Levinson *et al*. (2022)	AERA Open
Major *et al*. (2021)	British Journal of Educational Technology
Roshanaei *et al*. (2023)	Journal of Intelligent Learning Systems and Applications
Sierra *et al*. (2023)	Frontiers in Education
(Gunawardena *et al*., 2024)	Teaching and Teacher Education
Tengberg *et al*. (2024)	Teaching and Teacher Education

6.2 Citation distribution and academic influence: Analyzing the impact of research articles

The Table 2 presents the authors, publication years, and the number of citations for each study included in the current review, providing insights into the academic influence and relevance of each study within the context of AI-driven personalized learning and educational equity. Leslie *et al*. (2021) [21] stands out with 136 citations, indicating that this article is highly influential in the field. It likely addresses significant issues or offers critical insights that have resonated with other researchers, making it a cornerstone for understanding AI's role in education. Major *et al*. (2021) [24] and Levinson *et al*. (2022) [23] are also highly cited, with 112 and 50 citations respectively. These articles are likely pivotal in the ongoing discussions and research surrounding the integration of AI in educational contexts. Studies such as Doyle *et al*. (2022) [6] (24 citations), Das *et al*. (2017) [4] (15 citations), Bulathwela *et al*. (2024) [3] (14 citations), Roshanaei *et al*. (2023) [29] (13 citations), and Shanklin *et al*. (2022) [30] (12 citations) show moderate citation counts. These articles are recognized in the academic community but may be more focused on specific aspects of AI in education or newer contributions that are gaining attention. Several articles have very few citations, such as Wang *et al*. (2024) [37] (2 citations), Allotey *et al*. (2023) [1] (5 citations), and (Molla & Gale, 2023) [25] (6 citations). These may be more recent publications that have not yet had the time to accumulate citations or could be focused on niche topics within the broader field. Juhn *et al*. (2024) [15] and Sierra *et al*. (2023) [32] both have 0 citations, indicating that these studies are either very recent or not yet widely recognized in the academic community. The studies with low or no citations, such as Gunawardena *et al*. (2024) [9] (4 citations), Tengberg *et al*. (2024) [34] (1 citation), suggest emerging areas of research or new perspectives that are beginning to gain traction in the field (Table 2).

Table 2: Citation Distribution and Academic Influence: Analyzing the Impact of Research Articles

Code	Authors and year	Citations
A1	Wang *et al*. (2024)	2
A2	Das *et al*. (2017)	15
A3	Doyle *et al*. (2022)	24
A4	(Molla & Gale, 2023)	6
A5	Allotey *et al*. (2023)	5
A6	Juhn *et al*. (2024)	0
A7	Leslie *et al*. (2021)	136
A8	Bulathwela *et al*. (2024)	14
A9	Shanklin *et al*. (2022)	12
A10	Levinson *et al*. (2022)	50
A11	Major *et al*. (2021)	112
A12	Roshanaei *et al*. (2023)	13
A13	Sierra *et al*. (2023)	0
A14	(Gunawardena *et al*., 2024)	4
A15	Tengberg *et al*. (2024)	1

6.3 Key findings

The Table 3 summarizes key findings from various studies, providing a lens through which we can assess the role of AI-driven personalized learning tools in addressing educational inequities, particularly in STEM education. The analysis will focus on how these findings contribute to the overarching theme of creating just and inclusive learning environments through AI.

- **AI's potential in personalized learning:** Wang *et al*. (2024) [37] identifies critical areas where AI applications, such as adaptive learning and personalized tutoring, have the potential to revolutionize education by tailoring learning experiences to individual student needs. This is particularly relevant for STEM education, where personalized learning can help bridge the gap for students who may struggle with traditional, one-size-fits-all approaches. However, the study also highlights the underexploration of AI in early education and ethical considerations, signaling the need for careful implementation to avoid reinforcing existing biases. Das *et al*. (2017) [4] underscores the positive correlation between AI-driven personalization and improved academic outcomes. This finding is crucial for STEM education, as it suggests that AI tools can enhance student engagement and achievement, particularly in complex subjects like math and science. However, the study's limitations around generalizability suggest that more research is needed to ensure these benefits are accessible to all students, regardless of their backgrounds.
- **Addressing socioeconomic and racial biases:** Doyle *et al*. (2022) [6] brings to light the influence of socioeconomic status (SES) on teachers' judgments, which can lead to inequitable educational outcomes. In the context of AI-driven personalized learning in STEM, this finding is critical as it points to the potential for AI tools to either mitigate or exacerbate these biases. Ensuring that AI systems are designed to reduce SES-related biases could be key to creating more equitable learning environments in STEM fields.
  Shanklin *et al*. (2022) [30] highlights the risk of AI systems perpetuating racial biases, even when they are technically accurate. This is particularly concerning in STEM education, where underrepresented groups already face significant barriers. The study's proposed framework to decouple machine learning from optimization could be a valuable tool in ensuring that AI-driven personalized learning systems promote fairness and equity.
- **Ethical considerations and systemic challenges:** Leslie *et al*. (2021) [21] discusses the potential for AI systems to exacerbate existing inequalities, particularly in healthcare, but the insights are highly relevant to education. As AI becomes more integrated into STEM education, ensuring that these tools do not replicate or amplify existing disparities is critical. The study's emphasis on robust bias detection and community involvement in AI development offers a pathway toward more equitable AI systems. Bulathwela *et al*. (2024) [3] cautions against the risks of AI exacerbating educational disparities, particularly due to the digital divide. This warning is especially pertinent in STEM education, where access to technology can significantly impact learning outcomes. The study calls for the development of inclusive, human-centered AI systems that address these disparities, which aligns with the goal of creating just and inclusive learning environments.
- **Transformative approaches in educational equity:** Roshanaei *et al*. (2023) [29] provides a positive outlook on AI's potential to foster educational equity by offering personalized learning experiences tailored to individual student needs. This is directly aligned with the study's aim of leveraging AI to bridge educational inequities in STEM. However, the challenges mentioned, such as the digital divide and the risk of perpetuating biases, highlight the need for careful implementation and continuous monitoring to ensure these tools truly benefit all students. Molla & Gale (2023) [25] emphasizes the need for broader evaluative frameworks when assessing educational disadvantage. This perspective is essential for understanding how AI-driven personalized learning can be effectively used to address not just the symptoms of educational inequities in STEM, but their root causes. Expanding these frameworks can lead to more comprehensive and effective interventions.
- **Future directions for research:** Many studies in the table point to the need for future research to focus on long-term impacts, ethical considerations, and the development of more inclusive AI systems. For instance, Sierra *et al*. (2023) [32] and Gunawardena *et al*. (2024) [9] both call for broader research that includes diverse educational contexts and addresses the practical

challenges of implementing personalized learning at scale. These future research directions are crucial for ensuring that AI-driven tools in STEM education are designed and implemented in ways that are equitable and just.

Table 3: Key findings

Author and Year	Key Findings	Limitations and Future Research
Wang *et al*. (2024) [37]	The study provides a comprehensive review of AI applications in education, identifying four primary categories: adaptive learning and personalized tutoring, intelligent assessment and management, profiling and prediction, and emerging technologies. The most studied area is adaptive learning. The research highlights the importance of system design and implementation, with experiments being the predominant research method.	The study notes that AI applications in preschool education and ethical considerations are underexplored. It also highlights the lack of integration of the latest AI technologies like generative AI in the reviewed literature. Future studies should focus on exploring AI applications in preschool education, addressing ethical concerns related to AI in education, and integrating emerging AI technologies, such as generative AI, into educational research and practice.
Das *et al*. (2017) [4]	The study finds a positive correlation between AI-driven personalization in adaptive learning and improvements in academic achievement, learner engagement, and satisfaction. This suggests that personalized AI-based systems can significantly enhance educational outcomes.	The study may not fully account for the diversity of learners' needs and contexts, potentially limiting the generalizability of the findings. Future studies should explore the long-term impact of AI-driven personalization across diverse educational settings and examine ethical implications related to data privacy and algorithmic biases.
Doyle *et al*. (2022) [6]	The study found that teachers' judgments are influenced by students' socioeconomic status (SES), with lower SES students receiving lower grades and set placements compared to higher SES students, despite identical work. Interestingly, no significant racial bias was found, though the study suggests potential explanations for this lack of bias.	The study's limitation includes the potential for unmeasured biases influencing results, and the absence of racial bias could be due to social desirability or awareness among teachers. Future research should investigate the impact of teacher training on reducing SES-related biases and explore the complex interactions between race, SES, and teacher expectations in more diverse educational contexts. Additionally, examining how interventions could mitigate such biases would be valuable.
(Molla & Gale, 2023) [25]	The study argues for expanding the evaluative framework used by social researchers and policymakers when assessing educational disadvantage. It emphasizes considering not only the opportunities and outcomes but also the substantive nature of these opportunities and the conditions that influence how individuals convert resources into outcomes.	The limitation is the potential for a narrow focus in existing assessments, which may overlook important contextual and subjective factors. Future research should explore how these expanded evaluative spaces can be practically applied in policy and research to address educational inequity more comprehensively.
Allotey *et al.* (2023) [1]	The study found that Dialogic Literary Gatherings (DLGs) significantly transformed the educational experiences of marginalized students in Ghana. The DLGs provided a platform for students to engage in egalitarian dialogue, fostering mutual respect, self-confidence, and a sense of belonging. This led to improved relationships and attitudes among students, particularly those who had been marginalized.	The study was limited by its inability to measure the direct impact of DLGs on the academic performance of marginalized students, leaving an area unexplored in terms of quantifiable educational outcomes. Future studies should investigate the long-term impact of DLGs on academic performance and explore how this approach can be adapted and implemented in other educational contexts, particularly in different regions of Africa. Additionally, research could focus on integrating DLGs with other educational interventions to further enhance their effectiveness in addressing educational inequalities.
Juhn *et al*. (2024) [15]	The study identifies that artificial intelligence (AI) models in healthcare can exhibit performance disparities across socioeconomic status (SES) groups. The HOUSES index is presented as a validated tool for measuring SES in healthcare and detecting these biases. The study suggests that lower SES correlates with poorer healthcare data quality, which negatively impacts AI model performance for these groups.	A key limitation is the challenge of accurately measuring SES and its complex interactions with healthcare data quality and AI model performance. Future research should focus on refining SES measurement tools and developing AI models that are robust to disparities in data quality, particularly for lower SES groups. Additionally, exploring causal mechanisms behind SES-related biases in AI model performance would be beneficial.
Leslie *et al*. (2021) [21]	The study highlights that AI systems used in healthcare during the COVID-19	A significant limitation is the inherent bias in AI datasets and the lack of representativeness, which can lead to unequal outcomes for different

	pandemic risk exacerbating existing inequalities. These systems often reflect and amplify biases present in the data, disproportionately impacting marginalized and vulnerable communities.	sociodemographic groups. Future research should focus on developing AI systems with robust bias detection and mitigation protocols, ensuring inclusive community involvement in AI development, and addressing systemic inequities that contribute to health disparities.
Bulathwela *et al*. (2024) [3]	The study emphasizes the potential of AI in Education to revolutionize teaching and learning by creating personalized curricula and democratizing education. However, it warns that without addressing the digital divide and existing inequalities, AI could exacerbate educational disparities.	The primary limitation is the risk of AI perpetuating existing inequalities due to the digital divide and techno-solutionism, which could result in a misallocation of educational resources. Future research should focus on developing inclusive, human-centered AI systems that address the digital divide and promote equitable access to high-quality education for all learners. Additionally, it should explore how AI can be integrated with open educational resources to support emerging pedagogies and empower all stakeholders.
Shanklin *et al*. (2022) [30]	The study finds that AI algorithms, even when technically accurate, can perpetuate racial biases in medical appointment scheduling by disproportionately assigning Black patients to longer wait times. The study introduces a framework to decouple Machine Learning from Optimization to address such biases, demonstrating that fairness can be improved without sacrificing accuracy.	The framework may not be universally applicable across all AI systems, as it requires careful balancing between accuracy and fairness in different contexts. Future research should explore the application of this decoupling framework in other domains where AI is used, such as education and criminal justice, to mitigate biases and ensure equitable outcomes across diverse populations. Additionally, studying the long-term impacts of implementing such frameworks on both fairness and efficiency would be valuable.
Levinson *et al*. (2022) [23]	The article explores various interpretations and conceptions of educational equity, emphasizing that while equity is a widely lauded goal in education, it is also highly complex and often contradictory in practice. The authors identify at least five different conceptions of equity: equal outcomes across populations, equal outcomes for every child, equal resource allocation, equal experiences for each child, and equal levels of growth by each child. These conceptions are often linked to broader concerns, such as benefiting the less advantaged, ensuring educational adequacy, or prioritizing long-term structural change. The authors argue that understanding these distinctions is crucial for reimagining and restructuring unjust conditions in education.	The article acknowledges that it does not offer a comprehensive empirical analysis of all ways in which equity has been conceptualized in education. Instead, it provides a philosophical and conceptual analysis, which may not fully capture the practical complexities and challenges of implementing equity in diverse educational contexts. The discussion is also limited by its focus on the philosophical literature and may not fully engage with the broader empirical research on educational equity. The article suggests that future research could benefit from exploring how different conceptions of equity are operationalized in various educational settings and the trade-offs that educators and policymakers face when striving to achieve equity. It also calls for further empirical studies that examine the practical implications of these conceptual distinctions, particularly in terms of how they affect educational outcomes, resource distribution, and the lived experiences of students.
Major *et al*. (2021) [24]	The study conducted by Major *et al*. (2021) presents a meta-analysis on the effectiveness of technology-supported personalized learning in low- and middle-income countries (LMICs). The findings reveal that technology-supported personalized learning has a statistically significant positive effect on learning outcomes, with an effect size of 0.18. More personalized approaches, which adapt to learners' levels, had a significantly greater impact (effect size of 0.35) compared to those that only link to learners' interests or provide personalized feedback. Interventions were similarly effective for both mathematics and literacy, indicating that personalized learning approaches can be beneficial across different subjects. Whether or not teachers had an active role in the personalization did not significantly affect the effectiveness of the interventions. Additionally, moderate duration and intensity of technology implementation were found to have similar positive effects as stronger durations and intensities.	The study identifies several limitations. First, the meta-analysis includes studies from various countries, which introduces variability due to differences in educational contexts, technology infrastructure, and implementation fidelity. Second, although personalization features significantly impacted the effectiveness of interventions, the analysis did not fully account for the interaction between different contextual factors and these features. Lastly, there is potential for publication bias, as indicated by the funnel plot, although a trim-and-fill analysis did not suggest significant corrections were needed. The authors suggest several avenues for future research. These include investigating the cost implications of implementing personalized learning technologies at scale in LMICs. Further studies should explore the optimal length and intensity of personalized learning interventions to maximize their effectiveness. Additional research is needed to understand the role of teachers in personalized learning environments, particularly in terms of how their involvement can enhance or hinder the effectiveness of technology-supported interventions. Future studies should also consider the impact of personalized learning on broader educational outcomes, such as student engagement, motivation, and long-term academic success.

Roshanaei *et al*. (2023) [29]	The study "Harnessing AI to Foster Equity in Education" identifies the significant potential of Artificial Intelligence (AI) in promoting educational equity by facilitating personalized learning. Key findings include the ability of AI to customize educational content to suit individual students' learning patterns, strengths, and weaknesses, ensuring equal opportunities for all students to progress and excel, regardless of their starting point. Additionally, AI has the potential to bridge educational disparities by providing tailored instructional support that can help underserved or marginalized students catch up with their peers. The study reviews various case studies demonstrating how AI-driven platforms have successfully implemented personalized learning to enhance equity in different educational settings.	The study acknowledges several challenges and limitations in using AI to promote educational equity. A significant limitation is the digital divide, where students from low-income backgrounds may lack access to the necessary technology or internet connectivity required to benefit from AI-driven learning platforms. Additionally, AI systems may perpetuate existing biases if they are not designed and implemented with equity in mind, resulting in unequal outcomes for students from different demographic backgrounds. The successful integration of AI into educational systems also requires substantial investment in infrastructure, training for educators, and ongoing support, which may be challenging for resource-constrained environments. The authors propose several areas for future research. These include developing and testing methods for mitigating bias in AI algorithms to ensure that AI-driven educational tools promote rather than hinder equity. Research should also focus on the long-term effects of AI-driven personalized learning on educational outcomes, particularly for underserved or marginalized populations. Future research should explore strategies for scaling AI-driven educational interventions in a cost-effective and sustainable manner, particularly in low-resource settings. Additionally, investigating the perspectives of teachers and students on the use of AI in education can provide valuable insights into the practical challenges and opportunities for fostering equity through AI.
Sierra *et al*. (2023) [32]	The study "Development of the Teacher's Technological Pedagogical Content Knowledge (TPACK) from the Lesson Study: A Systematic Review" examines 16 studies from 2015 to 2021 on using Lesson Study (LS) to develop TPACK in teachers. Key findings include the synergy between TPACK and LS, a strong regional focus in Asia, predominance at secondary and higher education levels in disciplines like mathematics and science, and the dominance of qualitative research approaches, particularly case studies.	The study identifies several limitations. First, the systematic review did not find studies in Spanish that combine the TPACK and LS models, suggesting a language and regional bias in the available research. Second, the studies reviewed were primarily cross-sectional, limiting the ability to critically analyze long-term trends and effects of TPACK development through LS. Lastly, the review highlights a concentration of research in "hard sciences" like mathematics and science, with less focus on other subjects, potentially limiting the generalizability of the findings. The authors suggest several areas for future research. These include expanding research in other languages and regions, particularly in Spanish, to broaden the understanding of TPACK development through LS. Future research should also focus on longitudinal studies to better understand the long-term effects and trends in TPACK development using LS. Additionally, further investigation is needed into the role of expert professionals in LS, the cultural and pedagogical implications of LS in different contexts, and the teacher-researcher relationship within LS frameworks.
(Gunawardena *et al*., 2024) [9]	The study titled "Personalized Learning: The Simple, the Complicated, the Complex, and the Chaotic" investigates the perceptions of Australian secondary school teachers regarding the implementation of personalized learning using complexity theory as a framework. Key findings include that teachers generally understood personalized learning as a means to tailor learning experiences to individual student needs, strengths, and interests, and saw it as essential for addressing student diversity and equity. However, teachers expressed concerns and confusion about its practical implementation, particularly in managing large classes, adhering to a prescribed curriculum, and addressing varying student needs. The study found that implementing personalized learning was far more complex in practice than in theory, with teachers reporting difficulties in balancing personalized learning with curriculum demands and managing diverse student behaviors and needs.	The study acknowledges several limitations. First, the research was conducted with a small sample of seven teachers from a single school, which may limit the generalizability of the findings to other educational contexts. Second, the study was conducted in a specific regional and cultural context, and the findings may not be directly applicable to other educational systems or regions. Lastly, the study primarily focused on teachers' perceptions, without incorporating direct observations of classroom practices or student outcomes, which could provide a more comprehensive understanding of the challenges and opportunities of personalized learning. The authors suggest several areas for future research. These include expanding the research to include a larger and more diverse sample of teachers across different schools and regions to enhance the generalizability of the findings. Additionally, conducting longitudinal studies to examine the long-term impacts of personalized learning on student outcomes and teacher practices is recommended. Incorporating the perspectives of students to better understand how personalized learning affects their engagement, motivation, and academic achievement is also suggested. Finally, investigating potential strategies and solutions for overcoming the practical challenges of implementing personalized learning, particularly in relation to curriculum integration and classroom management, is proposed.
Tengberg *et al*. (2024) [34]	The study "The Impact of Observable and Perceived Features of Instruction on Student Achievement" investigates how observable teaching features (using the PLATO framework) and student perceptions (using the Tripod survey)	The study acknowledges several limitations. The sample size of 36 classrooms is relatively small, making the findings more vulnerable to random error and limiting their generalizability. Additionally, the observed teaching practices may be content-dependent, influencing the results based on the subject matter. The use of reading comprehension as the sole measure of student achievement may not fully capture the

	influence reading achievement in Swedish lower secondary schools. Key findings include that "Connections to Prior Knowledge," "Purpose," and "Classroom Discourse" significantly predicted reading achievement, explaining 4.3% of variance in post-test scores. Other observed features and student perceptions had limited impact, and significant gender differences were noted, with girls outperforming boys.	impact of teaching practices on broader educational outcomes. The authors suggest several areas for future research. These include involving larger samples and considering a broader range of student achievement measures to provide more robust and generalizable findings. Longitudinal studies should examine the long-term effects of observed teaching practices on student outcomes, incorporating multiple time points to better estimate growth and changes in student learning. Further studies should explore how teaching quality and its impact on student achievement vary across different educational contexts and subject areas to better understand the nuanced relationships between teaching practices and learning outcomes.

The studies reveal that AI-driven personalized learning tools can significantly improve academic outcomes, engagement, and provide tailored learning experiences, potentially bridging educational inequities in STEM education. However, risks like perpetuating biases, the digital divide, and ethical concerns about data privacy and fairness remain. To create inclusive STEM learning environments, these challenges must be addressed through careful design, rigorous research, and a commitment to equity. Future research should prioritize developing AI systems that are both technically proficient and socially responsible, ensuring equitable opportunities for all students in STEM fields.

6.4 AI-driven personalized learning in STEM education

As shown in Figure 2 and 3, the descriptive analysis of the demographic data from the survey shows several key points. Concerning institutions type, the majority of respondents (64 out of 150) work in private schools. Other institution types include public schools, online schools/virtual learning environments, and others (Figure 2). As for years of Teaching, the most common range of teaching experience is 4-6 years, with 69 respondents falling into this category (Figure 3).

These distributions provide a clear picture of the demographic characteristics of the educators participating in the survey, highlighting the prevalence of private school teachers and those with mid-level teaching experience. The survey's demographic data is essential for assessing the impact of AI-driven personalized learning tools in reducing educational inequities in STEM education. The type of educational institution influences the availability of resources and technology, affecting the effectiveness of AI tools. Respondent distribution across institutions highlights challenges and opportunities in diverse settings. Insights into grade levels emphasize the potential of AI tools in fostering STEM interest, particularly in middle school. Additionally, the teaching experience of respondents indicates varying levels of familiarity with integrating AI, emphasizing the need for tailored support and training for effective implementation.

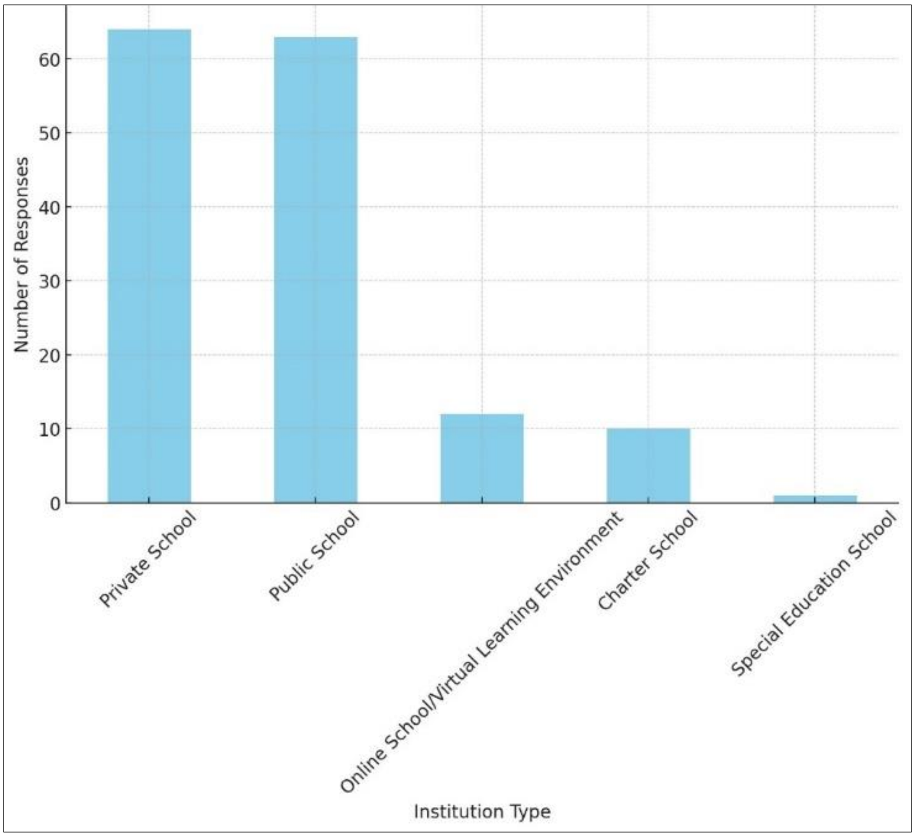


Fig 2: Distribution of Educational institution type

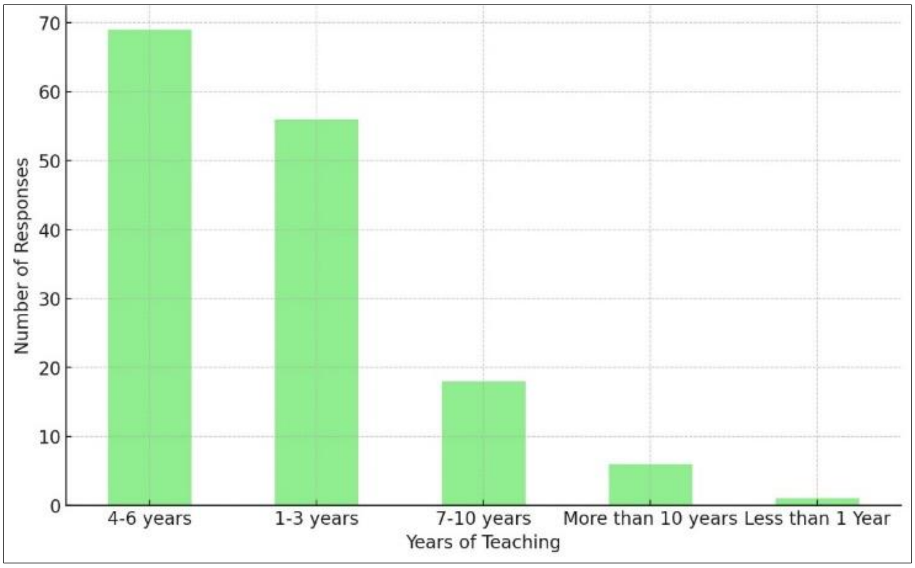


Fig 3: Distribution of teaching experience

In summary, the demographic data highlights that a diverse group of educators is involved in STEM education across various educational settings, with most having a solid educational background and varying years of teaching experience. This diversity is crucial when considering the implementation of AI-driven personalized learning tools. Such tools must accommodate the different needs of educators based on their experience, educational background, and the specific grade levels they teach. Furthermore, the varied responses regarding professional development and leadership support for STEAM education suggest that the successful integration of AI tools may require more consistent and targeted professional development opportunities. To bridge educational inequities in STEM, it is vital that AI-driven tools are implemented in a way that is accessible and beneficial across all types of schools and educational levels. This includes providing educators with the necessary training and resources to effectively utilize these tools.

7. Discussion

The findings from this study underscore the significant potential of AI-driven personalized learning tools in addressing and reducing educational inequities in STEM education. Through a comprehensive analysis of various research articles and the insights garnered from a systematic literature review, several key themes emerged that highlight both the opportunities and challenges associated with the integration of AI in education.

- **AI's potential in enhancing personalized learning:** The results reveal that AI-driven personalized learning tools hold substantial promise in enhancing academic performance, student engagement, and satisfaction, particularly in STEM fields. Studies like those by Wang *et al*. (2024) [37] and Das *et al*. (2017) [4] identified adaptive learning and personalized tutoring as crucial areas where AI can revolutionize education by tailoring learning experiences to meet individual student needs. These findings align with the theoretical framework of Personalized Learning Theory, which emphasizes the importance of adaptive learning environments that cater to diverse student needs. However, the underexploration of AI's application in early education and the ethical considerations highlighted by Wang *et al*. (2024) [37] signal the need for careful implementation strategies that prevent the reinforcement of existing biases.
- **Addressing socioeconomic and racial biases:** One of the critical objectives of this study was to explore the role of AI-driven personalized learning tools in mitigating biases related to socioeconomic status (SES), race, and access to technology. The findings from Doyle *et al*. (2022) [6] and Shanklin *et al*. (2022) [30] emphasize the nuanced impact of AI on educational equity. Doyle *et al*. (2022) [6] highlighted how SES can influence teachers' judgments, potentially leading to inequitable outcomes. The study suggests that AI tools, if designed with equity in mind, could mitigate these biases by providing objective, data-driven insights into student performance. However, Shanklin *et al*. (2022) [30] caution that AI systems, even when technically accurate, can perpetuate racial biases, underscoring the importance of integrating fairness and bias detection mechanisms into AI-driven educational tools.
- **Ethical considerations and systemic challenges:** The ethical implications of AI in education, particularly concerning data privacy and the potential for perpetuating existing inequalities, were recurrent themes in the analyzed literature. Leslie *et al*. (2021) [21] and Bulathwela *et al*. (2024) [3] both highlighted the risks associated with AI systems that amplify existing disparities, particularly due to the digital divide. These findings are particularly relevant within the context of STEM education, where access to technology plays a critical role in student success. The results suggest that while AI has the potential to democratize education, careful consideration must be given to its implementation to ensure that it does not exacerbate existing inequalities.
- **Transformative approaches in educational equity:** The potential for AI to foster educational equity by offering personalized learning experiences tailored to individual student needs is a key finding of this study. Roshanaei *et al*. (2023) [29] presented a positive outlook on AI's ability to bridge educational disparities by providing tailored instructional support that can help underserved or marginalized students catch up with their

peers. This aligns with the principles of Critical Pedagogy, which advocates for education that empowers marginalized communities. However, the challenges identified, such as the digital divide and the risk of perpetuating biases, highlight the need for ongoing research and development of AI tools that are not only technically proficient but also socially responsible.

- **Addressing educational inequities with AI-driven personalized learning: insights from institution type, grade levels, and teaching experience:** The finding that the majority of respondents work in private schools is significant, as these schools often have better access to technology, facilitating the adoption of AI-driven personalized learning tools. This advantage can lead to more innovative learning experiences but may widen the gap between private and public schools if not addressed. Public schools, serving diverse and underserved populations, face challenges due to budget constraints and lack of infrastructure. This highlights the need for scalable, cost-effective AI solutions that can be implemented across various institutions (Kamalov *et al*., 2023 [16]; Haefner *et al*., 2023 [11]; Woodruff *et al*., 2023) [38]. The distribution of grade levels taught by respondents provides insights into where AI-driven tools can have the most impact.
- Middle school is a critical period for STEM engagement, and personalized learning tools targeting this age group could sustain interest (Bhutoria, 2022; LeGeros *et al*., 2021) [2, 19]. The inclusion of educators from upper and lower elementary levels indicates an opportunity to introduce AI-driven learning early, building foundational STEM skills and addressing educational inequities from a young age. The finding that a significant portion of respondents has 4-6 years of teaching experience suggests that many educators are early in their careers but experienced enough to understand classroom challenges. These educators may be more open to adopting new technologies. However, it's crucial to consider the needs of more experienced educators, who may be resistant to change. Professional development and support must be tailored to meet the needs of educators across the experience spectrum, ensuring all teachers feel confident in using AI tools to enhance student learning (Hennessy *et al*., 2022; Howard & Mozejko, 2015) [12, 14].

8. Implications of this study

Theoretical Implications:

The study extends educational equity theory by exploring how AI-driven personalized learning tools can address disparities in STEM education, adding a new dimension to the discourse on educational equity. It provides a theoretical framework for integrating AI within existing pedagogical models, highlighting how AI can promote student engagement, differentiated instruction, and adaptive learning. Additionally, the study underscores the importance of transformational leadership in advancing educational innovation through AI, showing how leaders can foster a culture of continuous learning and adaptability crucial for successful implementation.

Practical Implications:

For educational practitioners and technology developers, the study offers actionable insights into the design and implementation of AI-driven tools, emphasizing adaptability to diverse educational environments and cost-effectiveness. Successful integration requires targeted professional development for educators, tailored to their experience levels and familiarity with technology. Policymakers can use these insights to advocate for funding and initiatives that support AI adoption in underserved schools, reducing educational disparities. School leaders can develop comprehensive plans integrating AI tools into the curriculum, fostering equity and inclusivity.

In summary, the theoretical implications enhance our understanding of AI's role in educational equity and leadership frameworks, while the practical implications provide concrete strategies for educators, policymakers, and school leaders to effectively implement AI-driven tools in STEM education. Together, these implications contribute to advancing both the theory and practice of leveraging technology to create more equitable and inclusive educational environments.

9. Conclusion

The study provides compelling evidence that AI-driven personalized learning tools have the potential to bridge educational inequities in STEM education by offering tailored learning experiences that cater to the diverse needs of students. However, the findings also highlight significant challenges, including the risk of perpetuating biases and the need for careful, ethical implementation of AI tools. To fully realize the potential of AI in creating just and inclusive learning environments, future research must prioritize the development of AI systems that are both equitable and accessible to all students, regardless of their background. The demographic insights from this survey highlight the challenges and opportunities of implementing AI-driven personalized learning tools in STEM education. Considering institution type, grade levels, and teaching experience can help design and deploy these tools equitably and effectively. The goal is to create a just and inclusive educational environment where all students can succeed in STEM, regardless of their background or school type. Targeted strategies are crucial to address specific contexts and bridge educational inequities.

Long-term impact and future research directions

The long-term impact of AI-driven personalized learning tools on bridging the achievement gap in STEM education remains an area ripe for further exploration. The findings suggest that while there is evidence of positive short-term outcomes, as noted in studies like Major *et al*. (2021) [24], there is a need for longitudinal research to assess the sustained impact of these tools on educational equity. Additionally, future research should focus on developing more inclusive AI systems that address the diverse needs of students across different socioeconomic backgrounds, as emphasized by Sierra *et al*. (2023) [32] and Gunawardena *et al*. (2024) [9].

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