WORKING PAPER

# ARTIFICIAL INTELLIGENCE & GENDER INEQUALITY IN EDUCATION:

## Evidence and Policy Implications for Africa


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# Abstract

Recent evidence indicates that the emergence of Artificial Intelligence (AI) is rapidly transforming education. However, evidence on the effectiveness of AI interventions in addressing gender inequality in education remains limited. In this regard, this study conducts a Systematic Literature Review on the role of AI in addressing gender inequality in education and draws implications for Africa. This study applies the PRISMA systematic review approach and synthesises evidence from peer-reviewed articles obtained from Scopus, Web of Science, and Google Scholar for the period 2015–2025. The review centred around themes: STEM and non-STEM fields; inclusive education for marginalised learners; algorithmic bias and equity concerns; and attitudes, confidence, and digital skills. The findings indicate that the adoption of AI can be a potent instrument for reducing gender gaps and expanding access to education, particularly for girls and women with disabilities. However, the review also suggests that the scalability of AI potentials has remained a significant challenge in Africa due to inadequate technological infrastructure and ingrained gender norms that often restrict its equitable implementation. One of the implications of these findings for Africa is that it points out that the implementation of ethical and responsible AI in the education sector by prioritising gender-sensitive design and infrastructure investment can be a potent tool for enhancing female participation in AI-enabled learning environments on the continent. In addition, this study contributes to the literature by providing a structured synthesis of global evidence and highlighting the contextual constraints that shape AI effectiveness in Africa.

# 1.Introduction

The use of Artificial Intelligence (AI) has received considerable attention in recent years. Also, AI technology is becoming increasingly adopted in the education sector for the purpose of improving the learning outcomes of the students. This is important given that in the presence of a significant gender gap and the digital divide, the adoption of AI can expand access to education for the marginalised groups. These groups include, but are not limited to, girls and women who face geographical, socio-economic, and disability-related barriers. For instance, the application of AI in personalised learning has been found to increase motivation and academic performance (Meena, 2015; Oztok & Zingaro, 2019). The AI in personalised learning analyses the learning styles of students and paces to deliver content that matches their needs. Similarly, intelligent tutoring systems, which provide a virtual teaching assistant to students in the absence of teachers, were found to support student learning outcomes (VanLehn, 2011). In addition, evidence indicates it reduces teachers' tasks, such as grading and note preparation, thereby giving them more time to engage with students (Oztok & Zingaro, 2019).

# 2. Incorporating AI in Africa's Education Sector

Artificial intelligence (AI) is steadily emerging as a powerful tool in Africa, with education becoming one of its most promising areas of expansion. Evidence from the African Union's Continental Artificial Intelligence Strategy explicitly prioritizes education as a sector for AI development, calling for competency frameworks, national strategies, and cross-country knowledge exchange to guide the responsible adoption of AI in schools across member states (IDRC, 2025). However, the strategy's high-level ambitions place significant demands on member states, as meaningful AI integration in education depends on the underlying technological infrastructure, which remains unevenly developed across the region. Many countries continue to struggle with unreliable electricity, limited broadband coverage, and insufficient data infrastructure, which restrict schools' ability to deploy AI tools at scale (African Union, 2024).

Limitations at the regional level extend beyond technological infrastructure to ingrained gender norms. A UNESCO (2020) report on AI and gender equality highlights that AI systems can reproduce or even amplify existing gender biases and discrimination through biased data, limited participation, and stereotypes, thereby widening instead of narrowing educational disparities for women and girls. In practice, this means that while the continental vision for AI in education is ambitious and forward-looking, it requires improved infrastructure and efforts that challenge existing gender norms that restrict inclusive learning.

# 3. Methodology

This section presents the methodology employed by this study to achieve its objectives. Before discussing the research design, it should be noted that the methodology is anchored in three complementary theoretical frameworks. First, this study applies the human capital theory as the framework to understand how investments in education and skills development can enhance individual productivity and long-term economic outcomes. Also, these improvements are important because they can create conditions that make increases in gender equality in education among the critical drivers of inclusive growth. Second, this study also relies on the prediction of the digital divide framework to understand how disparities in access to technology and digital literacy, as well as infrastructure, can reinforce existing inequalities, particularly across gender and geographic lines. Third, this study used the insights from algorithmic bias and socio-technical systems theory. Cumulatively, these models suggest that AI systems are not neutral; rather, they are also a reflection of data and institutional contexts in which they are developed. However, the framework suggests that while the adoption of AI has the potential to reduce gender disparities through personalised learning, it may also reproduce or amplify existing biases if not carefully designed. In this light, this study argues that together, these frameworks provide a conceptual basis for its understanding of both the opportunities and limitations of AI in addressing gender inequality in education in Africa.

## 3.1. Research Design

This study employs a systematic literature review (SLR) approach and synthesises global evidence on the impact of AI interventions on gender-related educational outcomes across diverse dimensions of learning. The choice of a systematic review was motivated by the recent rapid advancement of AI technologies and the expansion of its usage, but there exists a significant fragmentation of the body of research on its gendered implications on access and affordability of education. In addition, this study observes that the extant literature is currently dispersed across multiple thematic areas.

This dispersion often complicates efforts to draw consistent or generalizable conclusions. In this light, this SLR follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to ensure there is reliable and transparent reporting of the literature through four distinct stages: identification, screening, eligibility, and Inclusion (Rante et al., 2020; Moher et al., 2009). The application of this approach allows this study to collect, identify, analyse, and synthesise various related studies on AI interventions within education with respect to gender. Using the PRISMA process, this paper analyses 10 academic articles.

**Table 1:** Papers Analysed in the SLR

| No | Paper Title | Author Name(s) | Journal Name |
|---|---|---|---|
| **1.** | Can Artificial Intelligence Improve Gender Equality? Evidence from a Natural Experiment | Leo et al. (2024) | Management Science |
| **2.** | Computational Thinking and AI Literacy: A Gender-Based Analysis Among Early Learners | Cotin-Arbelo et al. (2025) | IEEE Global Engineering Education Conference (EDUCON) |
| **3.** | Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. | Zhang et al. (2023) | International Journal of Educational Technology in Higher Education |
| 4. | From Chalkboards to Chatbots: Evaluating the Impact of Generative AI on Learning Outcomes in Nigeria. (English) | De Simone et al. (2025) | N/A (World Bank Policy Research Working Paper No. 11125) |
| 5. | Is there a gender gap? A meta-analysis of the gender differences in students' ICT literacy. | Siddiq and Scherer(2019 ) | Educational Research Review |
| **6.** | AI Gender Bias, Disparities, and Fairness: Does Training Data Matter? | Ehsan et al. (2023) | Submitted to Educational Technology & Society |
| **7.** | A Review on the Feasibility of AI-Supported Education Platforms in Afghanistan: Addressing Barriers to Women and Girls' Education," | Karimy et al. (2024) | IEEE Global Humanitarian Technology Conference (GHTC) |
| **8.** | Enhancing Adaptive Learning with Generative AI for Tailored Educational Support for Students with Disabilities. | Nesren et al. (2025) | Journal of Disability Research |
| **9.** | Harnessing AI for Enhanced Student Learning and Performance in Higher Education: A Multinational Collaboration | Sing et al. (2025). | Indian Journal of Information Sources and Services. |
| **10.** | Gender Bias in Self-Perception of AI Knowledge, Impact, and Support among Higher Education Students: An Observational Study | Cachero et al. (2025). | ACM Transactions on Computing Education |

## 3.2. Study Identification and Selection (PRISMA)

This study searched various electronic databases of JSTOR, EconLit, ERIC (Education Resources Information Centre), Google Scholar, PubMed, ScienceDirect, and other relevant sources. These databases were selected because of their comprehensive coverage of relevant works on education, technological innovations, and interdisciplinary studies on AI and gender inequality in education. In the first step, this study retrieved about 1,247 records from the various databases. However, the application of the PRISMA framework led to the identification of 400 duplicate records. These 400 duplicates were removed, leaving 847 unique records for screening. In the second step, all the 847 titles, abstracts, and introductions were screened according to the inclusion and exclusion criteria (see Table 2). This screening resulted in the exclusion of 804 articles for several reasons, such as a lack of emphasis on AI in education (n=312), an absence of gender dimension (n=278), non-existence of empirical study (n=134), inappropriate publication type (n=48), language not English (n=18), and publication date not within the range of 2015 to 2025 (n=14). This process resulted in 43 articles for detailed scrutiny. However, additional screening led to the exclusion of 33 additional articles from the analysis for the following reasons: lack of emphasis on AI (n=10), lack of gender dimension (n=7), lack of empirical data or original study (n=9), lack of full-text articles (n=4), and inappropriate context outside education (n=2) and secondary sources such as systematic reviews or editorial pieces (n=1). In the final step, this process of selecting articles for inclusion in this study yielded 10 articles. These articles served as the basis for the qualitative synthesis of the role of artificial intelligence in addressing gender inequality in education, with particular attention to implications for Africa. In addition, Figure 1 presents the PRISMA flow diagram outlining the process for selecting articles for inclusion in the study.

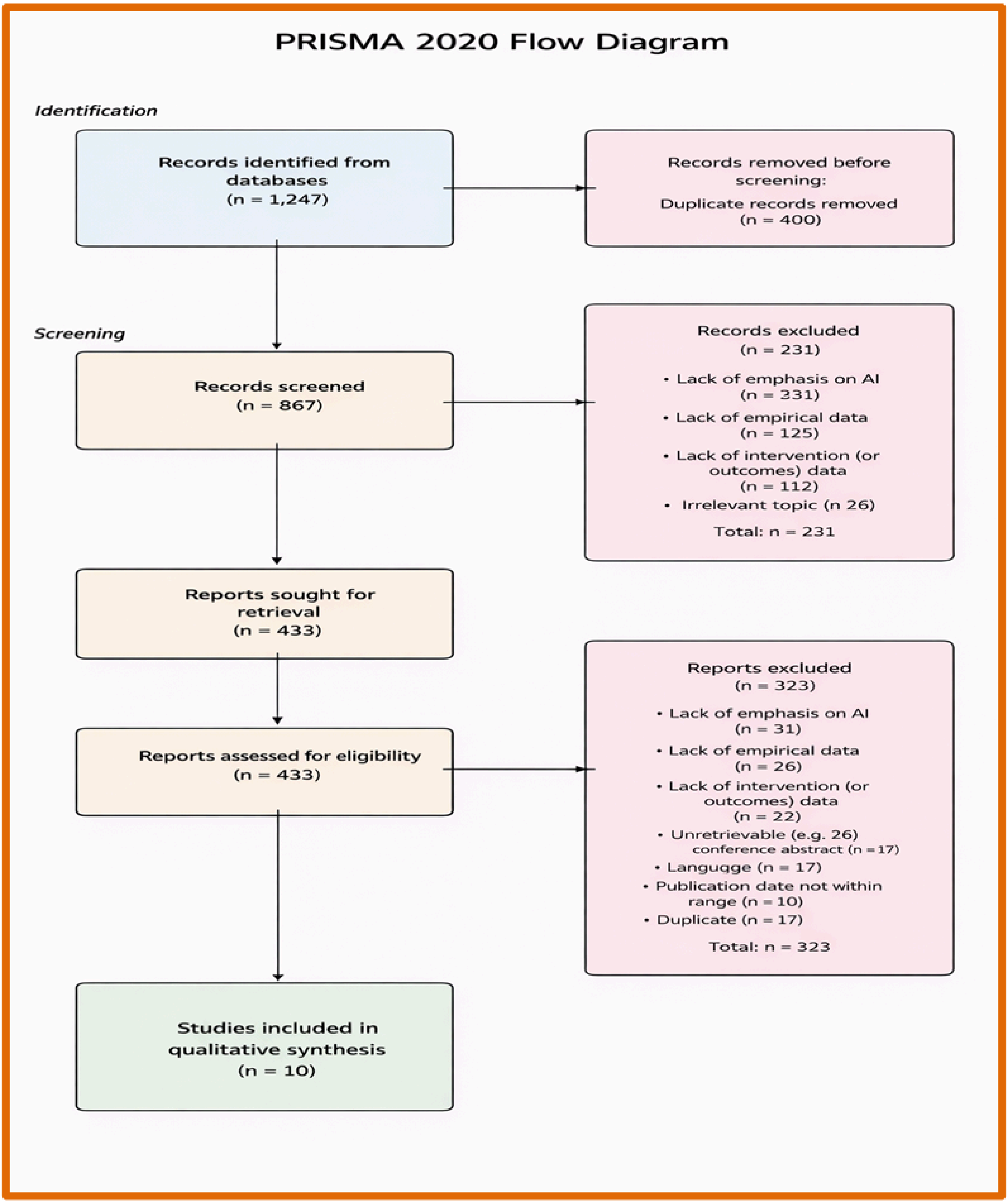


**Figure 1:**PRISMA 2020 Flow Diagram of the Study Selection Process.

**Table 2:** Inclusion and Exclusion Criteria

| No | Criteria Domain | Inclusion Criteria | Exclusion Criteria |
|---|---|---|---|
| **1.** | AI/Technology | Studies that substantively focus on artificial intelligence (AI) or machine learning technologies in educational contexts | Studies that lack emphasis on AI in education (AI not substantively addressed or only tangentially mentioned) |
| **2.** | Gender Dimension | Studies that explicitly examine gender-related outcomes, differences, or implications with substantive analysis | Studies that lack a gender dimension (gender not addressed or only superficially mentioned without substantive analysis) |
| **3.** | Research Design | Studies presenting original empirical research with primary data collection and analysis (quantitative, qualitative, or mixed methods) | Studies lacking empirical data or original research (purely theoretical papers, conceptual frameworks, no primary data) |
| 4. | Publication Type | Studies published in peer-reviewed journals or reputable conference proceedings | Inappropriate publication types (opinion pieces, editorials, commentaries, systematic reviews, meta-analyses, book reviews, or other secondary sources) |
| 5. | Publication Date | Studies published between January 2015 and December 2025 | Studies published before January 2015 or after December 2025 |
| **6.** | Full-Text Accessibility | Studies with full-text accessible and retrievable | Studies lacking full-text availability (the complete article could not be accessed or retrieved) |
| **7.** | Educational Context | Studies conducted in educational settings (schools, universities, online learning platforms, educational programs) | Studies in inappropriate contexts outside education |

# 4. Results

This section presents the findings from the SLR, highlighting how each paper's unique methodological approach contributes to these findings in light of the study's objectives. It is important to note that this section excludes the methodological details of the studies discussed in Sections 1, 2, and 3, as those were used solely to develop the conceptual and theoretical foundation necessary for addressing the core research questions of this study.

The review indicates that the empirical literature has employed a diverse range of methodological approaches to examine the implications of AI adoption in educational settings. Overall, Table 3 shows that four primary methodological categories are evident across the 10 studies: quantitative, mixed-methods, qualitative, and observational. Building upon these methodological foundations, table 4 shows the findings from the selected studies which are grouped into four main research themes: (a) STEM and non-STEM fields, (b) inclusive education for marginalized learners, (c) algorithmic bias and equity concerns, and (d) attitudes, confidence, and digital skills, which will be elaborated in subsequent subsections.

# 4.1. Methods Employed by Extant Literature

From Table 3, the evidence shows that the quantitative methods dominate the field, accounting for 60% of the selected studies, followed by mixed-methods (20%), qualitative methods (10%), and observational designs (10%). Six articles applied quantitative research designs to evaluate the relationship between AI interventions and gender-related educational outcomes. For instance, the study of Bao et al. (2024) conducted a natural experiment involving tournament data, video observations, and surveys to assess the impact of AI-assisted Go training on the performance of students and its gender dynamics. However, Table 3 shows that the study of Cotino-Arbelo et al. (2025) adopted a quasi-experimental pretest–posttest design to analyse extent of the gender differences in computational thinking and level of AI literacy among 114 preschoolers. Also, the table indicates that the study of Zhang et al. (2023) used an online survey of 452 pre-service teachers to model the factors that influence the intention to use AI-based educational applications and gender-based differences in behavioural determinants. A randomized controlled trial by De Simone et al. (2025) evaluated the effects of a six-week AI-powered chatbot intervention on English language proficiency among secondary school students, with specific attention to gender variation in outcomes. Siddiq and Scherer (2019) synthesised data from 23 empirical studies (N = 121,641) to evaluate gender differences in ICT literacy performance, focusing on foundational digital competencies relevant to AI-supported learning environments. In addition, Table 3 shows that the study of Ehsan et al. (2023) analysed over 1,000 student responses graded by human raters and large language models (BERT and GPT-3.5) to investigate how training data composition can shape gender bias in AI-powered scoring systems.

**Table 3:** Summary of Research Method Employed by Literature

| Research Approach | Collected Data & Instrument | Research Participants | Authors |
|---|---|---|---|
| Quantitative (n=6) | Natural experiment, tournament data analysis, video recordings, and surveys. | It compared 287 students taught by human teachers with others trained with AI | Bao et al. (2024) |
| | Quasi-experimental pretest-posttest design | It studied 114 pre-schoolers | Cotino-Arbelo et al. (2025) |
| | Online questionnaire | It studied 452 pre-service teachers | Zhang et al. (2023) |
| | Randomized Controlled Trial (RCT) | It studied 759 first-year senior secondary students who participated in a six-week English language learning program across nine public schools in Nigeria | De Simone et al. (2025) |
| | 23 empirical studies | It studied 121,641 students | Siddiq and Scherer (2019) |
| | Student-written responses, analyzed with BERT and GPT-3.5 models for gender bias in AI scoring | It studied more than 1,000 human-graded students | Ehsan et al. (2023) |
| Mixed-methods (n=2) | In-depth interviews and an online survey. | Collected data from 40 respondents, with a clear breakdown of gender distribution: 29 female, 7 male, and 4 who preferred not to disclose their gender | Karimy et al. (2024) |
| | Mix of large public datasets and synthetically generated data | It combined over 784,309 students from the EdNet dataset and more than 100,000 students from the ASSISTments dataset, totaling over 800,000 students in aggregate | Farhah et al. (2025) |
| **Qualitative (n=1)** | Open-ended, structured questionnaire distributed via Google Forms | It studied 29 postgraduate students (DBA and MBA) from Malaysia, India, and Iran were selected through purposive sampling. | Sing et al. (2025) |
| **Observational study (n=1)** | Structured questionnaire | 380 undergraduate students across various academic disciplines | Cachero et al. (2025 |

In addition, two studies were found to employ mixed-methods approaches to integrate quantitative measurement with qualitative insights. In this regard, Karimy et al. (2024) adopted an exploratory design of in-depth interviews and an online survey of 40 female respondents (predominantly).

It should be noted that this choice allows them to assess both the feasibility and accessibility to AI, as well as the gendered implications of education platforms supported by AI in Afghanistan. Also, Farhah et al. (2025) used a mixed-methods approach to evaluate an adaptive AI learning system using large-scale datasets (EdNet and ASSISTments), complemented with qualitative components to understand its accessibility, adaptability, and potential gender-based implications, even though the gender-specific results were not fully reported.

Furthermore, the remaining two studies used qualitative and observational methods. For example, the study of Sing et al. (2025) applied a qualitative design that involved purposive sampling of 29 postgraduate students (DBA and MBA) from Malaysia, India, and Iran to explore the perceptions of students about AI. In addition, the study focuses on moral responsibility, ethical considerations, effectiveness, and scalability. Also, Cachero et al. (2025) utilised an observational approach involving structured questionnaires administered to 380 undergraduate students across disciplines. This is to examine self-perceptions of AI knowledge, perceived impact, and available support, with a particular emphasis on gender differences in self-evaluated AI competencies.

Finally, the various research methods used in the reviewed studies indicate the extent of the complexity of research at the intersection of artificial intelligence, gender, and education. On the one hand, the analysis points out that the quantitative methods provide evidence of performance gaps, bias, and intervention effectiveness. On the other hand, this study observes that qualitative methods and observational studies appear to offer important insights into experiences and cultural factors. However, the mixed-methods studies were found to combine both quantitative and qualitative approaches. This blend allows the studies to quantify several outcomes and elucidate the mechanisms driving observed patterns.

## 4.2. Theme and Results of The Article Under Review

The methodological approaches reviewed in Section 4.1 demonstrate that there is a growing sophistication and diversity of empirical strategies employed to examine the gendered implications of AI in education. In addition, the predominance of quantitative and mixed-methods designs suggests there is emphasis on both measurable learning outcomes and nuanced contextual understanding. Also, the review observes that the application of the qualitative and observational studies was found to provide deeper insights into the perceptions of learners and their behavioural patterns, as well as ethical concerns. This methodological variety strengthens the evidence base, allowing for a more comprehensive interpretation of how AI shapes gender equality across different learning environments. Building on this foundation, the following section synthesises the substantive findings of these studies.

Also, it organised them around four major themes that capture the multifaceted ways AI influences gender dynamics in educational settings. The five main research themes in question are (a) STEM and non-STEM fields, (b) inclusive education for marginalized learners, (c) algorithmic bias and equity concerns, and (d) attitudes, confidence, and digital skills.

**Table 4:** The Research Theme of The Article Reviewed

| Theme | Key Findings | Authors |
|---|---|---|
| STEM and non-STEM | No initial difference in computational thinking skills between boys and girls. Following the intervention, girls significantly outperformed boys in computational thinking, challenging | Cotino-Arbelo et al. (2025) |
| | prevailing gender stereotypes. However, the intervention did not result in significant gender differences in AI literacy. | |
| | Girls achieved greater post-training improvements than boys when using AI-based education platforms in China. This suggests that AI may help reduce instructional bias by serving as a more neutral learning medium, particularly by supporting girls in a board-game environment traditionally dominated by males. | Bao et al. (2024) |
| | Students who received AI-driven chatbot interventions for English-language learning performed significantly better than those who did not receive the intervention, not only in English proficiency but also in AI knowledge and digital skills. Notably, girls, who initially lagged behind boys, recorded greater improvements, suggesting that generative AI may help narrow gender gaps in learning outcomes. | De Simone et al. (2025) |
| Inclusive Education for Marginalized Learners | Generative AI has the potential to transform learning experiences for students with disabilities, thereby promoting greater equity and inclusion in education. It further showed that AI tools can address long-standing accessibility barriers through features such as text-to-speech for learners with visual impairments, real-time captioning for those with hearing impairments, and speech recognition for students with limited mobility, allowing girls with disabilities to participate more independently in learning activities. | Farhah et al. (2025) |
| | Chatbots, generative AI tools, and SMS-based learning platforms can provide quality education for girls and women in displacement and crisis contexts where connectivity and technological infrastructure are limited. These affordable and adaptable tools were found to broaden access to education for marginalized populations frequently excluded from conventional education systems. | Karimy et al. (2024) |
| Algorithmic Bias and Equity Concerns | Mixed-trained models, using datasets with balanced gender representation, produced smaller mean score gaps and more equitable outcomes than models trained on gender-specific, unbalanced datasets, highlighting the significant impact of training data composition on gender bias in AI educational assessment tools. | Ehsan et al. (2023) |

| | | |
|---|---|---|
| | highlighting the significant impact of training data composition on gender bias in AI educational assessment tools. | |
| Attitudes, Confidence, and Digital Skills | When AI systems are trained on biased data, they can exacerbate or inadvertently perpetuate discrimination and inequality, including gender-based discrimination. | |
| | The study finds that female pre-service teachers are more prone to AI anxiety and that gender influences specific pathways within the AI acceptance model, suggesting that female pre-service teachers may be more apprehensive about using AI-based applications in their teaching and learning. This greater anxiety of female pre-service teachers is attributed to cognitive and non-cognitive factors, including less prior experience in STEM fields, greater risk aversion, and gender stereotyping. | Bao et al. (2024) |
| | Significant gender disparities in how higher education students perceive AI, with females generally exhibiting lower self-perceptions of AI knowledge and ability, greater concerns about personal data, and less overall enthusiasm and support for AI development than males. | De Simone et al. (2025) |
| | Female learners exhibited a small but statistically significant advantage in actual ICT literacy performance, contradicting previous self-report studies suggesting that boys had higher self-efficacy and more favourable attitudes toward technology. | Farhah et al. (2025) |

## 4.2.1. STEM and Non-STEM Fields

The evidence in Table 4 suggests that the adoption of AI appears to influence the extent of gender disparities in learning outcomes across both the STEM and non-STEM domains. Also, the evidence points out that as AI-driven tools reshape instructional delivery, AI interventions can be a significant factor in narrowing gender performance gaps. Also, this was found to be more plausible in environments where girls have traditionally been disadvantaged in terms of access to education (Cotino-Arbelo et al., 2025). Cotino-Arbelo et al. (2025) show that girls, who initially performed at similar levels to boys in computational thinking, achieved substantially higher scores after the intervention, indicating that AI-supported learning may counteract entrenched stereotypes in technology-related subjects. There is concern, however, that these gains may not automatically translate into broader improvements in AI literacy, as the study reports relatively uniform digital skill enhancements across genders.

Similarly, the study of Bao et al. (2024) finds that AI education platforms in China tend to enable girls to outperform boys following the training phase. This evidence is a reflection of the potential of AI in reducing instructional biases that often favour male learners in competitive academic settings. The implications of these results may be more pronounced in contexts where gendered expectations strongly shape learner engagement. On the other hand, De Simone et al. (2025) demonstrate that AI-powered chatbots in language learning environments generated greater improvements for girls, leading to narrower gaps in both linguistic proficiency and digital engagement.

Nevertheless, a qualification emerges from these studies: while AI-supported systems consistently reduce gender gaps in performance, improvements in foundational AI literacy are not always significant or evenly distributed. This suggests that complementary interventions may be necessary to ensure that advances in academic outcomes are matched by gains in broader digital competencies (Bao et al., 2024; Cotino-Arbelo et al., 2025; De Simone et al., 2025).

## 4.2.2. Inclusive Education for Marginalised Learners: Disabilities and Conflict-Affected Contexts

The review observes that two studies have their key focus on populations that are systematically excluded from traditional educational settings. For example, Farhah et al. (2025) show that AI-assisted adaptive learning systems significantly improve access and engagement for students with disabilities. This is because it provides features such as text-to-speech and real-time captioning, as well as speech recognition. In addition, the study of Karimy et al. (2024) highlights the role of AI chatbots and SMS-based platforms in delivering education to girls in crisis-affected and displacement contexts. The evidence from this study demonstrates that AI can expand access to education where infrastructure is limited. One of the implications of the findings of these studies is that they point out that AI can enhance equity and inclusion by enabling participation for learners traditionally marginalised due to disability, geography, or conflict. However, the effectiveness of these interventions was found to be highly context-dependent and constrained by infrastructural limitations (Farhah et al., 2025; Karimy et al., 2024).

### 4.2.3. Algorithmic Bias and Equity Concerns

The review suggests that sometimes AI platforms can induce some forms of algorithmic bias. For example, the study of Ehsan et al. (2023) demonstrates that balanced datasets produce more equitable outcomes, but unbalanced data was found to exacerbate gender gaps. Also, Sing et al. (2025) show that AI can inadvertently reproduce existing social and cognitive biases. This ability often reinforces inequalities in access to education, among others. One of the implications of this evidence is that it suggests that the impact of AI on gender equality depends critically on dataset composition and system design, as well as institutional context. Also, this evidence highlights the need for inclusive design practices and monitoring to mitigate algorithmic bias (Ehsan et al., 2023; Sing et al., 2025).

### 4.2.4. Attitudes, Confidence, and Digital Skills

The review shows that studies examining attitudes toward produce evidence indicating that there is a performance–confidence paradox in the AI application. For example, the study of Zhang et al. (2023) reports that female pre-service teachers are more prone to AI anxiety. This was found to be influenced by cognitive and non-cognitive factors such as risk aversion and prior STEM experience. In addition, Cachero et al. (2025) find that female students perceive their AI skills as lower and express more concern about privacy, despite comparable engagement. Additional analysis by Siddiq and Scherer (2019) finds that female students exhibit a slight advantage in actual ICT performance, contradicting self-perceived confidence. One of the implications of these findings is that they point out that gender differences in attitudes and confidence may persist even when performance is equal or superior. Also, they suggest that AI interventions alone are insufficient to address socio-cultural and psychological barriers to education (Zhang et al., 2023; Cachero et al., 2025; Siddiq & Scherer, 2019).

# 5. Discussion

Overall, the thematic review suggests that AI serves a dual role in education. On the one hand, the evidence suggests that it can enhance learning outcomes and reduce performance gaps for female learners. On the other hand, the analysis shows that its impact is mediated by infrastructural, socio-cultural, and algorithmic factors (Bao et al., 2024; De Simone et al., 2025; Ehsan et al., 2023; Karimy et al., 2024).

This evidence implies that a successful implementation requires addressing these contextual constraints to fully leverage AI for gender equity in educational settings in Africa. In addition, the studies selected for this systematic review provide consistent evidence that artificial intelligence (AI) interventions can positively impact gender equality in education, although the magnitude of effects varies across contexts. From Table 4, the evidence shows that across diverse thematic areas, AI-based educational tools generally improve learning outcomes of females and, at the same time, expand access for the marginalised populations. However, effectiveness depends on structural and contextual factors, including digital infrastructure, socio-cultural norms, and data quality (Karimy et al., 2024; Farhah et al., 2025). The themes highlight the multifaceted nature of AI's influence on gender equality in education, ranging from direct improvements in academic performance to broader issues of access, bias, and digital literacy.

# 6. Conclusion

This study conducted a systematic literature review (SLR) that investigates the potential role of artificial intelligence (AI) in addressing gender inequality in education. To achieve this objective, this study draws from global evidence from studies published in reputable international journals from 2015 to 2025. The review analysed 10 articles, and the studies were selected based on predetermined criteria to identify, classify, and synthesise the research findings. The findings of this review were found to provide important information on current trends in the usage of AI along the four main themes: STEM and non-STEM fields; inclusive education for marginalised learners; algorithmic bias and equity concerns; and attitudes, confidence, and digital skills. In general, the findings suggest that AI can be a potent instrument in reducing gender gaps and also in expanding access to education for marginalised groups, including girls and women with disabilities. This was observed to be achieved by offering personalised learning and overcoming traditional barriers. However, this review also observes that the full potential of AI appears to be hindered by significant challenges, particularly in Africa, where there is the prevalence of inadequate technological infrastructure and ingrained gender norms that often restrict its equitable implementation. In addition to these regional challenges, the evidence suggests that AI systems can reproduce or amplify existing gender biases through biased data and entrenched gender norms. Thus, for Africa to implement ethical and responsible AI in the education sector, the evidence from this review suggests that it is essential to prioritise balanced training data, gender-sensitive design, and investment in technological infrastructure.

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