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Adaptive AI Tutors in African Classrooms: A Systematic Literature Review on Personalised Learning

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ABSTRACT

Artificial intelligence (AI) tutors are gaining traction in African education to facilitate personalised learning, feedback, evaluation, and educational access. However, the evidence available is dispersed in terms of country, level of education, technology and context of implementation. This systematic literature review aimed to aggregate evidence regarding types, educational impacts, implementation conditions and sustainability of adaptive AI tutors and personalised learning systems in African education in the period 2019- March 2026. The review was designed to combine the Scientific Procedures and Rationales for Systematic Literature Reviews with the PRISMA 2020 reporting guidelines. A total of 312 records were found in the databases searched, 54 of which were duplicates, 258 were screened, and 26 studies were included in the final analysis. The accompanying research studies included secondary, primary, basic, vocational, teacher, engineering, and higher education settings, and focused on the use of intelligent tutoring systems, adaptive learning platforms, mobile AI tutors, educational robotics, generative AI, predictive analytics, and AI-supported assessment. Overall, the evidence suggested gains for learner engagement, personalised pacing, formative feedback, academic outcomes, and teaching efficiency, but the extent and ability to generalise findings across studies were highly variable. The need for greater connectivity, a reliable electricity supply, devices, teacher preparation, funding, data privacy concerns, algorithmic bias, and cultural and linguistic localisation were recurrent barriers to implementation. The review shows that the interaction of adaptive technological functions, active participation of the learner, the facilitation of the teacher and the enabling institutional conditions pave the way for the emergence of educational results based on Programmed Logic for Automatic Teaching Operations and Constructivist Learning Theory. This study brings an Africa-centred Science and Technology framework depicting the mobile compatibility, contextual localisation, ethical regulation and human-in-the-loop model as the most likely features of adaptive AI tutors that will support equitable learning.

I. INTRODUCTION

Artificial Intelligence (AI) is revolutionising the traditional classroom environment, reshaping the future of learning and moving learning away from the teacher-centralised approach to a data-driven, personalised journey uniquely tailored to each learner. With the application of intelligent technologies, the ability of adaptive AI(AAI) tutors to provide real-time guidance and support to teachers is one of the most exciting new developments in the field of education [1], [2], [3]. In Africa, where educational inequalities are further worsened by teachers' shortages, restricted learning materials, overcrowded classrooms and urban–rural differences, AAI can address these challenges by reimagining education and learning through scalable personalised education [4], [5], [6], [7].

Even with these global progressions, the educational advantages of AI that adapts have not been uniform around the world. Although the use of AI in personalised learning is growing in the context of technological advancement in education systems, there are contextual challenges in Africa regarding infrastructure, digital readiness, adoption of policies and preparedness of teachers. Therefore, it is crucial to understand how adaptive AI tutors can be successfully adopted in African classrooms. Recent interventions exemplify the increasing integration of various AI tutoring technologies into educational contexts, including AAI tutors, adaptive learning platforms (ALTs), Intelligent Tutoring Systems (ITS), mobile AI tools and educational robotics in countries such as Kenya, Nigeria, Ghana, Zambia, South Africa and Rwanda. The technologies make use of learner modelling, predictive analytics and real-time feedback to personalise learning and learning progress by catering to learners' abilities, preferences and progress, which facilitates self-directed learning and competency-based progression [1], [8], [9], [10]. Model compression and mobile-first design have also allowed for the deployment of sophisticated AI systems on low-cost smartphones to provide access to communities that don't have access to digital infrastructure in traditional devices [11], [12].

Empirical evidence indicates that AAI tutors can significantly benefit learning outcomes in Africa. Implementations of mobile AI have been reported to increase learner engagement, boost mathematics and STEM outcomes, enable personalisation of pacing and accelerate vocational skill acquisition, with some reported as having increased skills acquisition with very high accuracy in the operations [8], [11], [13], [14], [15]. Instead of replacing teachers, AI is becoming a powerful instructional ally that streamlines routine feedback and assessment tasks while allowing teachers to engage in higher-order interactions and pedagogical mentoring [16], [17], [18].

While these are positive steps, the evidence base remains insufficient and there are limitations to be overcome for successful implementation. Numerous implementations are limited to short-term pilots or isolated institutional projects and do not offer reliable insight into their longer-term educational effectiveness or scalability. Additionally, there are concerns about the funding limitations. lack of infrastructure, connectivity issues, unreliable electricity supply, inadequate teacher training, algorithmic bias and data privacy concerns that pose a threat to equitable use in various African contexts[5], [9], [19], [20], [21]. Studies conducted so far tend to be country- and/or technology-specific, making it difficult to obtain a holistic picture of AAI tutors' performance in the context of education in Africa [2], [22].

As a result, there is a significant gap in knowledge about the types of AAI used in schools, the levels of educational effect found and the factors required for successful deployment within specific contexts. Otherwise, policy makers, schools, developers and researchers will be less likely to develop an intervention that is educationally effective, ethically acceptable and feasible in resource-poor settings. Earlier reviews have contributed to the understanding of the development of artificial intelligence in the education field; however, the scope of these reviews did not fully cover the problem investigated in the present study. While some reviews have taken a broad global perspective and included evidence from both high-income and low-income contexts, others have constrained their exploration of the factors that drive the implementation of AI in African education systems to infrastructural, pedagogical, linguistic, and governance factors. Other reviews have targeted specific technologies, for example, the use of intelligent tutoring systems or generative AI, and focused mainly on higher education instead of exploring the use of adaptive AI in a wider range of educational contexts. As a result, dimensions such as unequal connectivity, unreliable electricity supply, mobile-device dependence, teacher preparedness, indigenous-language support, cultural localisation, and long-term institutional sustainability have been treated as secondary implementation issues rather than as interacting dimensions of educational effectiveness [2], [5], [21], [23], [24].

TABLE 1
PRESENT REVIEW VERSUS PREVIOUS REVIEWS

Review dimension	General emphasis in previous reviews	Contribution of the current review
Geographical focus	Global review or combined developed and developing-country evidence	Exclusive focus on African educational contexts
Technologies	Generative AI, general AI, or a single technology	Adaptive learning platforms, ITS, mobile AI tutors, generative AI, educational robotics and adaptive assessment
Educational levels	Predominantly higher education or a single educational sector	Integration of primary/basic, secondary, TVET, teacher preparedness,

		engineering and higher education
Teacher role	Acceptance, adoption or replacement concerns	The teacher's role is analysed as a mechanism linking AI functionality with learning outcomes.
Infrastructure	Often treated as a background limitation.	Analysed as a moderator of access, educational effectiveness and continuity
Equity	Broad discussion of access	Analysis of rural access, digital inequality, gender inclusion, device dependence and affordability
Cultural localisation	Limited treatment	Examination of curriculum alignment, culturally relevant data, contextual appropriateness and indigenous languages
Theoretical interpretation	Largely descriptive or technology-oriented	Incorporation of PLATO and Constructivist Learning Theory in coding, synthesis and interpretation
Main output	General synthesis	Proposed Africa-centred socio-technical framework for adaptive AI implementation

What is evident from Table 1 is that the novelty of the present review does not just stem from studying AI in Africa. The value added by it is in the development and facilitation of technological mechanisms and the incorporation of learner-centred pedagogy, teacher facilitation, infrastructure, equity, governance, and cultural localisation at the various educational levels. While some reviews give good descriptions on the adoption of AI and the development of educational technology, there are fewer that consider these two components as an interconnected socio-technical system in the African educational context [5], [7], [19]. Consequently, the resulting synthesis goes beyond simply detailing the tools available for AI and provides a framework for how adaptive AI is likely to yield meaningful, equitable, and sustainable education.

The present review seeks to overcome these limitations. It brings together work from primary or basic education, secondary education, technical and vocational education and training, teacher education, engineering education and higher education. It also provides an analysis of the technological characteristics, the learners' outcomes, the role of the teacher, the infrastructure, the equity, the ethics, the governance, and the cultural responsiveness in one synthesis that is based in Africa. This study focuses on how the adaptive technological mechanism interacts with pedagogical and contextual conditions, and what kinds of educational outcomes are generated, unlike most of the previous reviews that mainly list AI applications or report on general trends of adoption. It thus presents an African perspective on how, when, and in what context adaptive AI tutors can aid personalised learning in African classrooms, informed by theory. This systematic literature review aims to answer the following research questions that aim to close this gap:

- What are the AAI tutors and personalised learning systems that have been adopted in African schools and through which technological approaches?
- What evidence exists of their consequences on academic performance, learner engagement, skill acquisition and the changing role of the teacher?
- What are the infrastructural, socio-cultural, financial and ethical challenges and opportunities for the effective implementation and sustainability of AAI tutors in Africa?

Theoretically, the review was based on Programmed Logic for Automatic Teaching Operations PLATO) and Constructivist Learning Theory (CLT). The principles of computer-assisted instruction (CAI) with adaptive sequencing, automated feedback and learner profiling, which are fundamental to PLATO, form the basis of many of today's ITS [3], [8], [14]. The view is complemented by the philosophy of Constructivist Learning Theory (CTL), where knowledge is actively created, students construct their own knowledge, student progression is based on competency and learning is adaptive, which are all principles that are used in the implementation of modern AI-based personalised learning in countries like Rwanda and South Africa [9], [10], [15]. The study conceptualises AAI technologies as tools that can enhance learning outcomes through personalisation of instruction and conditions such as teacher facilitation, infrastructure readiness[7], [12], ethical governance and cultural localisation [17], [19], [25].

The merit of this study lies in its comprehensive synthesis of new evidence on AAI tutors across various educational contexts in Africa (2019-March 2026). The study brings together the results of different nations, technologies and education levels, enriching the understanding of pedagogical, technological and governance aspects of AI-supported personalised learning. The review further builds on existing scholarship by offering an Africa-centred perspective that connects adaptive technologies to their contextual implementation needs, thereby offering policymakers, educators, developers and researchers actionable ideas for promoting equitable, human-centred and sustainable integration of AI in education.

Based on the literature reviewed, it is evident that there has been a significant amount of work in developing and applying adaptive AI tutors in the education sector in Africa. The findings are clear that progress is being made on aspects of learner engagement, personalisation of learning and academic outcomes, but that there are some ongoing issues with infrastructure, teacher readiness, ethics and contextualisation.

While the findings offer valuable insights into current developments, a theoretical perspective is needed to explain how adaptive AI technologies support personalised learning and the reasons behind the different implementation outcomes in various educational contexts. Therefore, the theoretical background to this study is presented in the next section.

The rest of the study is presented as methodology, results, Discussion and Conclusions.

A. *Theoretical Framework*

This study is based on two complementary theory perspectives, namely PLATO and CLT. These theories collectively offer a comprehensive framework for understanding the role of AAI tutors in engaging learners, tailoring instruction to learners and aiding knowledge building in African educational settings. PLATO is built on the technology and instructional mechanisms of ITS, such as automated sequencing and individualised feedback. In contrast, CLT is based on the idea that learners construct understanding through adaptive, learner-centred experiences. The combination of these theories provides a holistic framework for understanding how AAI tutors are used and their impact in various learning contexts—a computer-based system designed for the automation of education.

1) PLATO: PLATO was among the first substantial large-scale applications of CAI and was the precursor of today's ITS. According to [3], [14], the core idea behind PLATO is to use automated instruction, branching logic, continuous assessment, immediate feedback and personalised learning paths based on student performance to improve learning. These ideas are very similar to the "learning personalisation" capabilities of modern AAI tutors, which continually evaluate the learner's interactions to tailor content, task level and learning paths. The theoretical framework of PLATO can be useful to comprehend the ways that AI tutors can resolve the issues brought by restricted training materials and a lack of skilled teachers in African countries. The evidence presented in this paper shows that ITS used in higher education institutions like Ashesi University in Ghana and Mangosuthu University of Technology in South Africa can deliver personalised pacing, profiling of learners and immediate corrective feedback, leading to enhancement of learner engagement and academic performance [8], [14]. Similarly, Kenya and Nigeria have witnessed the development and application of compressed mobile AI models in vocational education, demonstrating the opportunities of automated tutoring systems in resource-limited environments that achieve high performance and reach. Similarly, compressed mobile AI models have been developed and deployed in vocational education in Nigeria and Kenya and have demonstrated high performance and reach in the context of limited resources [8], [11]. This is why PLATO provides the technological mechanisms by which AAI tutors operate, including tracking learner progress, providing timely interventions and optimising instructional sequencing. It also aligns with the perspective that AI should be used to complement rather than substitute for teachers, taking on routine teaching tasks and allowing more time for facilitating learning and supporting students [3], [16]. PLATO describes the technological processes by which adaptive systems can personalise instruction and address the needs of learners. Still, it offers relatively little explanation of how learners actively build knowledge as a result of these interactions. It is therefore necessary to have an educational learning theory to complement the technological perspective provided by PLATO.

2) CLT: The CLT postulates that people learn by constructing knowledge by interacting, reflecting and having previous experiences as well as meaningful learning activities. Learning is understood as a socially situated, individualised process, where learning trajectories should reflect differences in learners' backgrounds, abilities, interests and learning trajectories and instructional strategies should be adapted accordingly. Constructivist principles are well suited to AAI tutors, as it is natural for the tutors to tailor learning activities based on the needs of each learner, offer scaffolding feedback and enable students to learn at their own speed [9], [10]. Rather than provide the same instruction to all students, AI systems continuously modify instruction to best meet the needs of students by analysing their mastery and misconceptions and by using performance data. This personalisation empowers learners to take ownership of their learning, fosters self-regulation and competency-driven advancement and nurtures a stronger engagement with learning material. This alignment is supported by evidence collated during this review. AI-powered adaptive teaching is applied to personalised learning in Rwanda, where it improves learner motivation and achievement by adapting learning to the individual learner and giving instant feedback, for example [9], [15]. A similar approach of individualised learning pathways was found in the use of ALPs in science classrooms in South Africa, which also supports differentiated teaching and continual improvement of learning [10], [13]. The next example of personalised mathematics teaching in secondary schools in Kenya also demonstrates how learner-centred learning approaches enhance the ownership of learning and academic performance [13]. CLT is therefore the pedagogical explanation as to why AAI tutors are helpful in educational outcomes. When instruction is adaptive and allows learners to have their cognitive and contextual needs addressed uniquely, then they are more likely to succeed.

3) Integrating PLATO and Constructivism: While PLATO and CLT have their own different intellectual traditions, they complement each other in describing AAI-supported learning. While PLATO focuses mainly on the computational aspects of adaptive tutoring (automated sequencing, learner models and intelligent feedback mechanisms), Constructivism focuses mainly on the educational processes through which learners gain from personalised engagement, personalised participation and knowledge constructed in a personalised way. The combination of technological intelligence and pedagogical approaches that are learner-centred is proposed as a key condition for AAI tutoring to be considered successful. The personalisation is delivered via AI algorithms that constantly analyse learner data and constructivist principles that ensure that personalisation is used to facilitate meaningful learning and not simply for content delivery. Thus, the effectiveness of AAI tutors depends not only on the sophistication of the algorithms but also on the design of the instruction, facilitation of the teachers, curriculum alignment and interaction of learners. This approach is mostly relevant in the case of education in Africa, where the application of adaptive technologies must be aided by teaching approaches that acknowledge the context of learning, considering local features and limitations such as infrastructure and linguistic diversity. Existing literature found that AI support helps achieve better results when it is teacher-supported, culturally responsive and integrated with local curricula, as opposed to simply relying on AI technology [5], [17], [19].

4) Proposed Conceptual Framework: Informed by PLATO and CLT, the review defines AAI tutoring systems (with examples such as Adaptive Learning Platforms (ALP), ITS, mobile AI tutors and educational robotics) as the principal enabling technologies that provide personalised learning through features of adaptive content sequencing, learner modelling, pacing, predictive analytics and real-time feedback. They shape these processes in the middle of the learning process, such as engagement, self-directed learning, motivation, formative assessment and facilitation by the teacher. These, in turn, help to produce educational outcomes like better academic performance, faster learning, better skills acquisition, better competency building and better teaching effectiveness. Yet, these relationships are being constrained by context-specific issues of digital infrastructure, power supply for electricity and connectivity, teacher professional learning, funding sustainability, ethical governance, data privacy protection, algorithmic fairness, curriculum alignment and cultural responsiveness. The works of Vygotsky on the Zone of Proximal Development (ZPD) and Rogers on the Diffusion of Innovations theory were applied to interpret the claim of cognitive development and technological readiness. The ZPD theory of Vygotsky and the Diffusion of Innovations theory of Rogers were used to interpret the claims of cognitive development and technological readiness.

5) Application of PLATO and Constructivism to the review: The coding system used was deductive and inductive. The deductive codes were drawn from PLATO, such as adaptive sequencing, automated feedback, learner profiling and progression based on performance and from Constructivist Learning Theory, such as active learning, scaffolding, autonomy, reflection and teacher facilitation. These inductive codes emerged from repeated occurrences of evidence relating to infrastructure, affordability, governance, cultural localisation, gender inclusion, data privacy, and sustainability. The coded evidence was then categorised into categories of mechanism, process, outcome, and contextual-moderator. This process made it possible to apply the theories to the interpretation and interrogation of the results, but not to have the theories "post hoc" introduced into the discussion. PLATO and Constructivist Learning Theory were used as analytical frameworks as well as background theories. PLATO assisted with the coding of technological and instructional functions, such as modelling and presenting to the learner, adaptive sequencing, automated feedback, monitoring performance, formative assessment, and competency-based progression in the process of data extraction. These codes enabled understanding of the ways in which adaptive AI systems modified the instructional content, pacing, difficulty, and feedback, based on learner performance. Constructive Learning Theory was used to code processes that are considered learner-centred and pedagogic processes such as active knowledge construction, learner autonomy, self-directed learning, collaboration, engagement, scaffolding, reflection and teacher facilitation. The evidence was then reviewed to assess if adaptive AI was simply a way to deliver information or to allow learners to engage in some form of personalised learning task.

II. METHODOLOGY

This systematic literature review (SLR) is aimed at synthesising and critically analysing the existing literature on the implementation and effectiveness of adaptive Artificial Intelligence (AI) tutors and personalised learning systems in the context of education in Africa. For this reason, a systematic literature review (SLR) was chosen as a research method that provides a transparent and replicable method for identifying, appraising and synthesising results across multiple studies and reduces researcher bias. The systematic review methodology differs from traditional narrative review in that it is based on a set of predetermined procedures used to select, extract and synthesise data, thus providing more reliable and evidence-based conclusions. In the evolving landscape of AI technologies and the inconsistent findings of studies conducted in various countries and sectors on the continent, a systematic review is considered to be a suitable methodology to build a body of knowledge about the current state of the science and identify gaps.

For literature published between 2019 and March 2026, a systematic search was carried out in all the databases actually searched. The search period was chosen to reflect the current proliferation of adaptive learning platforms, intelligent tutoring systems, generative AI, mobile AI, and other personalised learning technologies based on data in African education. Searching was done on the title, abstract and keywords fields, if available, in the respective database. The following words were used in the core search string; adaptive AI, personalised education, educational context, Africa: (“adaptive artificial intelligence” OR “adaptive AI” OR “intelligent tutoring system” OR “AI tutor” OR “adaptive learning platform" OR "adaptive learning system" OR "personalised learning platform" OR "personalised learning system" OR "educational robot" OR "mobile AI tutor" OR "AI-supported feedback" OR "AI-assisted assessment") AND Any words that include the term "education" or "classroom" or "school" or "university" or "higher education" or "vocational education" or "TVET"). AND (Africa OR Sub-Saharan Africa OR names of African countries). The search syntax was adjusted to suit the indexing rules of each database in such a way that there was no change in underlying logic. The reference lists of eligible publications were used for backward reference searching and newer publications that cited relevant foundational publications were found through forward citation searching. All retrieved information was sent to the Mendeley software. Automated and manual duplicate checking was done on the basis of title, author, year, DOI and information from the source of publication.

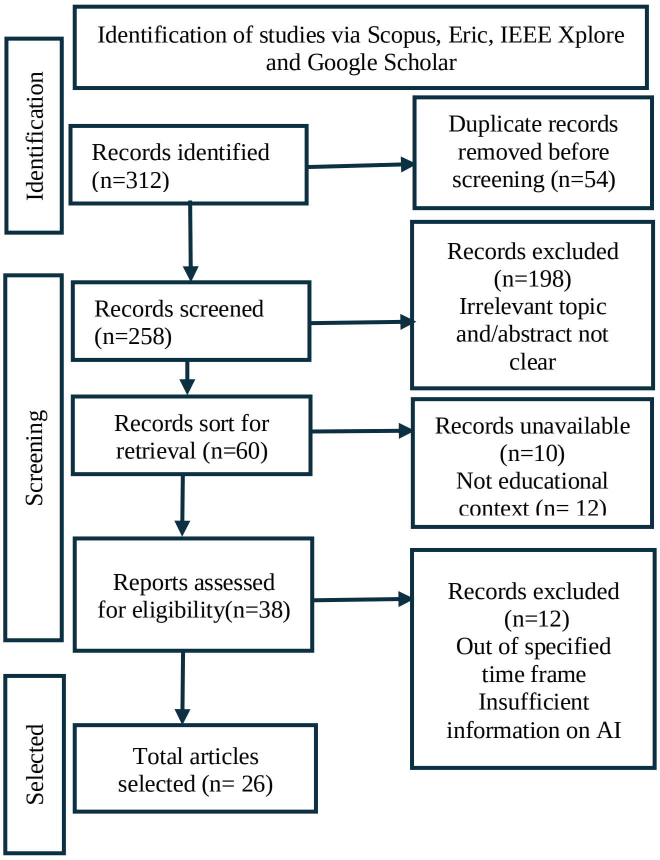

Figure 1. PRISMA flow chart.

To strengthen the methodological rigor, the Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) was used in combination with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [26]. The strategic framework for planning the review, its scope, the organisation of the evidence and the synthesis of findings into meaningful themes was provided by SPAR-4-SLR. To ensure transparency in study identification, screening and eligibility assessment and final inclusion, PRISMA, Figure 1, complements this process by providing a standardised reporting protocol. The use of these frameworks has been growing in the number of truly high-quality review studies, as it increases the reproducibility of the studies and provides both methodological and conceptual rigor.

The first search returned 312 articles. Following duplicate removal (n=54), title/abstract screening (n=198 excluded) and full-text eligibility (n=26 included), the result of the synthesis was a set of 26 studies. This process was carried out after PRISMA had identified, screened and selected the eligible papers and SPAR-4-SLR had passed through the assembling, arranging and assessing stages.

A. *Integration of SPAR-4-SLR and PRISMA*

The sole difference between the two was that they were complementary, but different, in the reviewing process of the programme. The overall methodological approach to the design and implementation of the review was guided by the assembling, arranging and assessing phases, as carried out by SPAR-4-SLR. Study inclusion and exclusions were documented using the PRISMA 2020 reporting and audit tool. The review goals, research questions, search time, information sources, search strings and eligibility criteria were determined during the assembling phase. PRISMA helped with this step by mandating clear data reporting of how many and where records were found. In the arranging phase, characteristics of the studies were retrieved and sorted by country, education level, research design, AI technology, learning domain, and reported outcomes. In the assessing phase, methodological characteristics of the studies were evaluated and the evidence was thematically synthesised based on PLATO and Constructivist Learning Theory categories. PRISMA supplemented these activities by capturing the progression of records in screening and by asking for justification for excluding full texts. As such, the planning, organising, appraising and synthesising of the review were guided by the principle of SPAR-4-SLR, and the reporting of the search and selection process was guided by the principle of PRISMA 2020. They helped to improve the conceptual organisation and the repeatability of the review. Table 2 presents the integration process.

TABLE 2
INTEGRATION TABLE

Review procedure	**SPAR-4-SLR stage**	**PRISMA function**	**Output**
Formulating questions	Assemble	Review rationale	Research Questions
Formulating search terms and selecting databases	Assemble	Search strategy and information sources	Replicable search protocol

Duplicate removal and screening	Assemble	Identification and screening	PRISMA diagram
Developing study characteristics	Arrange	Data item reporting	Characteristics table
Study grouping	Arrange	Synthesis preparation	Context, level, technology and methodology
Study quality appraisal	Assess	Risk-of-bias reporting	Thematic findings according to the theory
Exclusions reporting		Eligibility report	Inclusion and exclusion table

1) *Identification stage*: PRISMA identification phase involved the planning of the review goals, search approach, search terms and eligibility criteria. In this phase, relevant publications were identified and relevant duplicates were removed according to the titles and abstracts of the publications using PRISMA screening. The Identification stage was used to define the scope of the review and to keep all activities in line with the study goals. The review offered a glimpse into the evolving landscape of African education, featuring significant developments in AI and generative AI technologies, like intelligent tutors, adaptive learning systems and mobile education tools from 2019 to March 2026. The time frame (2019 – March 2026) was chosen to document the latest wave of adaptive AI interventions in African classrooms, as generative AI and mobile-first deployments ramp up. While there are continued studies that will support the numbers in 2026, it was considered appropriate to forward include to capture new pilot projects and policy initiatives. The technologies explored included ITS, ALP, AI-powered chatbots, mobile AI tutors, educational robotics and compressed AI models for low-resource settings. Key words were used to search and were combinations of the following keywords: adaptive artificial intelligence, ITS, ALP, personalised learning, AI tutors, educational robotics, mobile AI technologies and Africa. Alternative terms and synonymous terms were taken into account to maximise retrieval and minimise the chance of missing papers. This study was limited to predominantly adaptive systems that can adapt instruction or provide specific feedback to learners, excluding classic educational technologies that cannot be adapted. Therefore, reference lists of eligible studies were hand-screened by backward citation tracking and forward citation searches were conducted to find more recent papers that cited foundational studies. This iterative search process meant that seminal and emerging contributions were taken into account to enhance the comprehensiveness of the evidence base.

Three research questions were used to guide the planning stage:

- What are the AAI tutors and personalised learning systems that have been adopted in African schools and through which technological approaches?
- What evidence exists of their consequences on academic performance, learner engagement, skill acquisition and the changing role of the teacher?
- What are the infrastructural, socio-cultural, financial and ethical challenges and opportunities for the effective implementation and sustainability of AAI tutors in Africa?

These questions guided the search strategy, inclusion criteria, data extraction process and the thematic synthesis.

2) *Screening Process*: All retrieved studies were subsequently screened in a systematic way to eliminate any studies that were not in line with the aims of the review. First, duplicate records were removed and then titles and abstracts were analysed to determine the preliminary relevance. At this point, publications that addressed general educational technologies but not AAI, non-African contexts, or non-educational applications were eliminated. Studies reporting empirical evidence, implementation experiences, evaluation findings and systematic analysis of AAI in the field of education were prioritised in the screening process. The publications had to discuss one or more of the following factors of learner outcome, teacher support, infrastructure, implementation challenges, governance and ethics. This multiple-stage screening process ensured that literature irrelevant to the review questions was excluded, while studies that could contribute to the review questions were included. “

3) *Eligibility Assessment:* The number of published papers on the use of AI in education across Africa has also increased significantly during this time, particularly between 2024 and 2025, as the academic and research interest in this field of personalised learning technologies has grown across the region, as seen in Figure 2. The eligibility assessment entailed a thorough review of the full texts of all potentially relevant studies. The methodological quality, contextual relevance, clarity of AI implementation, reported educational outcomes and discussion of the barriers to implementation and/or ethics were assessed for each article. Special care was taken to ensure that adaptive technologies were actually implementing aspects of learner modelling, personalised instruction and dynamic feedback and not just digitising traditional learning materials. The review took an inclusive approach, acknowledging that AI in African education is a nascent field of study despite the diversity of methods used. Contextually relevant implementation studies and exploratory investigations were selected when they provided useful evidence for technology implementation and/or teacher experience and/or implications for policy and their limitations were taken into account when interpreting. Table 3 presents the inclusion and exclusion criteria.

TABLE 3
INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	Exclusion criteria
Adaptive AI tutors, mobile AI models, ITS, robotics, ALTs	EdTech without adaptive AI
African studies	Not in Africa
2019- March 2026 period	Outside 2019-March 2026
Studies with empirical evidence, evaluation or systematic reviews	Purely conceptual/ not implemented, editorial opinion papers
Focus on personalised learning.	General ICT application
Intelligent AI in education	Studies reporting on educational outcomes, or implementation experiences of non-education-related AI applications

The synthesis was based on 26 studies obtained after applying the eligibility criteria. This final selection of 26 studies only partially illustrates the emergent and also geographically limited state of studies on adaptive AI tutors in African education because of the breadth of evidence produced. This is not an arbitrary cap on the number of studies included but rather a reflection of the emerging and geographically uneven state of studies on adaptive AI tutors in African education. While 312 records were found, most papers focused on general educational technology, did not focus exclusively on African contexts, did not concern themselves with the use of AI in education, and did not include a focus on opinion-based discussions. The studies retained were from a variety of educational levels, from primary, secondary, technical, vocational education and higher education institutions and from Nigeria, South Africa, Ghana, Zambia, Zimbabwe, Rwanda, Kenya and multi-country African or regional contexts. For a structured qualitative synthesis, with the aim of identifying technological patterns, implementation conditions, reported outcomes and evidence gaps, a corpus of 26 studies is enough. However, the corpus should not be taken to represent the education systems or all African countries uniformly. Conclusions are limited to patterns within the published evidence available and not generalised across the entire continent. This relatively small and geographically limited evidence base is also a critical insight and an indicator of the need for further longitudinal and comparative studies in underrepresented African regions. In addition, the range of selected studies allowed for comparison across technologies, pedagogical approaches, infrastructure conditions and governance frameworks and offered broad enough representation to identify themes and patterns that emerged across the continent.

4) *Data Extraction*: A standard data extraction template was prepared in advance of the selected studies in order to ensure consistency and transparency. The information gained from each publication covered bibliographic information, country of implementation, educational level, type of AI technology used, research methodology, reported learner outcomes, implementation barriers, ethical considerations and principal conclusions. The structured extraction matrix enabled a systematic comparison of the heterogeneous studies, minimising the risk of selective interpretation. It also allowed evidence to be categorised into similar themes that could be synthesised thematically. Table 4 presents the data extraction framework.

TABLE 4
DATA EXTRACTION FRAMEWORK

Data element	Purpose in analysis
Author and year	Chronological analysis and citation
Country of study	Regional comparison
Educational sector	Contextual classification
AI technology	Type of technology used
Research design	Methodological analysis
Learning outcomes	Evaluation of effectiveness
Implementation barriers	Identification of contextual constraints
Main findings	Cross-study thematic synthesis

5) Quality assessment: Quality appraisal was used to assess the credibility and trustworthiness of the evidence included. The methodological transparency, empirical robustness, contextual relevance and reporting quality of implementation and ethics of each study were evaluated. Rigorous evaluation designs and intervention descriptions in quantitative studies that used AAI were especially useful for interpretation. Importantly, quality assessment did not exclude findings from the weightings or interpretations; instead, it informed the weightings and interpretations. This approach acknowledges that in new technological areas, there may be exploratory and implementation research that yields valuable contextual information, even if the research methods vary.

The methodological quality of all the included studies has been critically appraised, before the data synthesis, to guarantee methodological rigour and the evidential credibility of the findings of the review. A review-specific risk-of-bias instrument was created as the review included publications from several types of designs, not just a single one; it was not possible to use one specific risk-of-bias instrument for the design. This method is advised for systematic reviews that are collating heterogeneous evidence with a variety of study designs [24], [26]. Each study included was assessed independently using five methodological criteria, taken from guidelines for conducting systematic reviews [24], [26]: clarity of research aim/ objective; appropriateness and transparency of the research design; adequacy of the data source, participants, or sample; The accuracy and reliability of the analysis performed and results presented; and The relevance of the evidence for the implementation of adaptive artificial intelligence in African education. A 3-point scale was used to score each criterion:

0 = Not addressed

1 = Partially

2 = Adequately addressed,

giving a maximum possible score of 10 for each study. Studies with a score of

8-10 were considered high,

5-7, moderate and

0-4, low.

To ensure as complete a representation of adaptive AI in African education as possible, another method of exclusion was not based solely on quality appraisal, as there is a significant number of implementation reports, policy analyses and initially few empirical studies on adaptive AI in the field of education in Africa. In contrast, thematic synthesis was informed by methodological quality in determining weights of evidence. The level of confidence in the conclusions drawn from findings was higher if they were based on high-quality studies, and lower if they were based on moderate- or low-quality studies[26]. All studies were independently reviewed by the review team and appraised based on the pre-determined criteria to ensure reliability of the process. Disagreements over points were discussed to reach an agreement and minimize subjective judgment in the assessment of studies [26].

6) Data synthesis: The synthesis process began with repeated reading of the literature extracted as evidence to become familiar with it. A snippet of data from the literature is presented in Table 5 on the supplementary page

The characteristics of the 26 studies used in this systematic literature review are summarised in Table 5. The body of evidence is composed of publications between 2020 and March 2026, which show the rising scholarly interest in the use of adaptive artificial intelligence (AI) in African education in relation to the escalating digital transformation efforts and the need for personalised learning [13], [23]. They come from a variety of educational environments in South Africa, Kenya, Rwanda, Ghana, Nigeria, Zambia, and elsewhere in Sub-Saharan Africa, reflecting the growing regional interest in investigating the role of AI in teaching and learning, albeit in different environments with varying levels of educational infrastructure and technological maturity [8], [9], [27].

The reviewed studies spanned various educational levels such as primary education, secondary education, technical and vocational education and training (TVET), higher education, and across the educational sector. The highest number of studies in the evidence base focused on higher education, including many studies on the use of intelligent tutoring systems and adaptive learning platforms in universities [8], [14], [15]. The second largest category was secondary education, in which focus was mostly put on personalised mathematics teaching, learning companions with AI and adaptive learning systems [13], [28], [29]. Fewer studies explored the use of AI in primary schools and TVET institutions, indicating that evidence on the use of AI in foundational and vocational education is still relatively less developed[11], [30].

Methodologically, the evidence base was very diverse, including various types of quantitative studies, as well as qualitative studies, mixed methods, case studies, systematic reviews, conceptual papers, implementation studies, and policy analyses. This methodological variety helped to integrate empirical evidence on the effectiveness of education with the broader contexts of implementation, governance and policy making. While most empirical studies tested adaptive AI technologies in the classroom, interventions or pilot projects, or case studies of institutions, most systematic reviews and policy-oriented publications offered strategic insights regarding AI readiness, governance and educational transformation in Sub-Saharan Africa [10], [15], [31].

The adaptive AI technologies examined were: intelligent tutoring systems (ITS); adaptive learning platforms (ALPs); mobile AI tutors; AI learning companions; educational robotics; AI-assisted assessment systems; and generative AI applications. The majority of the technologies examined and discussed were intelligent tutoring systems and adaptive learning platforms, which are commonly used to support learner modelling, personalised learning, adaptive feedback, and competency-based progression [8], [9], [14]. Recent research has featured the use of AI tutors on mobile devices as well as small, lightweight adaptive systems suitable for low-resource educational contexts in Africa, such as Kenya, Nigeria, and Zambia, which underscores a new focus on technology's affordability and accessibility in education systems across the continent [11], [12], [29].

The time of interventions was very different among empirical studies, ranging from brief classroom-based interventions (weeks) to extended implementations (semesters). But relatively few studies had designs that included more than one school year. Despite the evidence being consistently positive in terms of the short-term benefits of adaptive AI tutors on learner achievement, engagement and personalised learning, there is not enough empirical research on the long-term sustainability, scalability and institutional impact of adaptive AI tutors in an African context [13], [15], [29].

The overall methodological quality of the evidence was also satisfactory, as reflected by the quality appraisal. Most of the studies included in the analysis achieved high ratings (8–10), indicating strong statements in all four categories of research quality: research objectives, methodological designs, analytical procedures, and relevance to adaptive AI in African education. Moderate quality studies tended to have small sample sises, poor methodological reporting or narrow implementation scope, with a small number of low quality studies. Quality appraisal was not used as a criterion to exclude studies from the synthesis. Still, it was used to weigh the evidence for thematic synthesis to ensure that conclusions were based on the most methodologically sound evidence, with the implementation and policy evidence that was contextually important from this relatively new field.

In addition, the features of the studies included indicate that the field of research into adaptive AI in African education is developing in a variety of educational sectors, learning areas and technological applications. Despite this, the evidence is focused on higher education; most studies are short-term in nature, and there are few multi-country and large-scale longitudinal studies, suggesting key areas for future research. The reviewed studies offer a wide and methodologically sound body of evidence for exploring the educational effectiveness, implementation considerations, governance and contextual issues that arise for the use of adaptive AI technologies in African education systems [2], [23], [27].

For themes, generated through narrative synthesis, initial codes were created that represented technologies, outcomes, facilitating factors of implementation and governance issues and subsequently clustered together in broader conceptual categories. These categories were refined through an iterative process of comparing studies to develop themes that reflect overarching patterns while providing nuance on important context-specific differences. Lastly, the constructed themes were interpreted in the light of PLATO and CLT to hypothesise a linkage between adaptive technologies, pedagogically oriented towards the learner and educational outcomes. framework. Table 6 presents themes generated through narrative synthesis.

TABLE 6
THEMES GENERATED THROUGH NARRATIVE SYNTHESIS

Theme	Explanation
Adaptive AI technologies	Examines ITS, adaptive learning platforms, chatbots, educational robotics and mobile AI tutors used across African education. Chronological analysis and citation
Educational effectiveness	Synthesises evidence relating to learner achievement, engagement, motivation, personalised instruction and skill acquisition.
Teacher roles	Explores how AI augments educators through automated feedback, assessment and instructional support rather than replacing them
Infrastructure and resource constraints	Investigates the influence of connectivity, electricity, hardware availability and financial sustainability on implementation success.
Ethics and governance	Analyses data privacy, transparency, algorithmic fairness, accountability and responsible AI practices.
Cultural responsiveness	Examines curriculum localisation, linguistic adaptation, culturally relevant content and contextual appropriateness of AI systems.

Coding was undertaken in an inductive manner, starting with descriptive codes (e.g., teacher facilitation, infrastructure barriers) and moving to analytical codes (e.g., equity challenges, algorithmic bias). Triangulation of the various studies and consistency with the PLATO and CLT principles were used to validate the theme. The resulting logical analysis is then: The adaptive AI mechanism is connected to the learner-centred educational process, which leads to the educational outcome influenced by the contextual conditions.

7) Analytical framework: The final step was incorporating the generated evidence into an analytical framework to relate technological ability to educational outcomes. The analysis identified AAI mechanisms (e.g., learner modelling, adaptive sequencing, predictive analysis and real-time feedback) as processes that act as enablers to shape learner engagement, personalised instruction and formative assessment. These intermediate mechanisms were later followed by the broader educational outcomes, such as an increase in academic success, increased motivation, faster progress and better educational equity. In addition, the framework acknowledged that the contextual factors that influence these relationships are infrastructure readiness, teacher preparedness, curriculum alignment, ethical governance, data quality and cultural localisation. Also, this analytical approach helped identify patterns and trends that went beyond individual findings, revealing how pedagogical, technological and contextual factors contribute to the successful implementation of AI in African education. Table 7 presents the analytical synthesis matrix

TABLE 7
ANALYTICAL SYNTHESIS MATRIX

AI mechanism	Intermediate Educational Process	Intended Outcome	Key Moderating Factors
Learner modelling	Personalised instruction	Improved academic performance	Teacher readiness
Adaptive sequencing	Self-paced learning	Greater mastery	Curriculum alignment
Real-time feedback	Formative assessment	Increased engagement	Infrastructure quality
Predictive analytics	Early intervention	Reduced learning gaps	Data quality
Mobile AI deployment	Expanded access	Educational inclusion	Connectivity and device availability
Offline AI capability	Learning continuity	Equity in low-resource settings	Electricity and technical support

8) Trustworthiness and Rigor: Several complementary approaches to enhancing the credibility of the review were tried. All steps of evidence collection and analysis were managed by a pre-established review protocol and inclusion and exclusion criteria were transparent to reduce the risk of selection bias. The use of standardised extraction templates ensured consistency among the reviewers and allowed the process to be reproduced. The systematic planning and synthesis provided by SPAR-4-SLR contributed to reporting transparency, while the integration of PRISMA added to this. Lastly, theoretical triangulation using PLATO theory and Constructivist Learning Theory gave a lens of interpretation that gave the synthesised findings conceptual coherence and increased explanatory power.

Methodological contribution: In addition to summarising the existing body of evidence, this study shows that the use of SPAR-4-SLR is a useful complement to PRISMA in reviews of new educational technologies. The overall methodology is transparent and theory-informed and will incorporate a variety of evidence that is heterogeneous but still methodologically rigorous. The methodology provides a robust framework for policymaking, research and the responsible adoption of adaptive AI in African education systems, with a structured approach that connects the three main components: adaptive AI technologies, pedagogical processes and contextual moderators, while tying them to educational outcomes. Systematically selected and rigorously evaluated body of evidence with the use of the SPAR-4-SLR framework and PRISMA reporting guidelines. The literature synthesised serves as empirical evidence to uncover common themes across technological, pedagogical, infrastructural and governance aspects of adaptive AI tutors in African classrooms. The results are shown in the next section.

B. Evidence Mapping of the Included Studies

An evidence mapping analysis was undertaken to present a visualisation of the evidence base, based on the key characteristics of the studies included in the evidence base summary (Table 5), in a supplementary page. In recent years, evidence mapping has become a common technique in systematic literature reviews to help understand the maturity and scope of a research field by highlighting patterns in publications over time, areas of countries' focus in publications, methodological approaches and technological focus within the chosen research field [26]. Figure 2 in the supplementary file shows three complementary heat maps, highlighting the distribution of adaptive AI research in African education in terms of country of study and publication year, country and research methodology, and country and AI technology. Together, these visualisations offer a snapshot of the development of research in the field of adaptive AI in African education contexts and identify gaps in empirical studies.

Panel A shows the distribution of studies included by country of study and also publication year (2020-March 2026). Panel B shows the country-wise distribution of research methods, while Panel C depicts country-wise mapping of AI technologies explored in each country/regional context. The colour intensity shows the number of studies in each topic; darker colours signify a higher number of studies.

The number of published papers on the use of AI in education across Africa has also increased significantly during this time, particularly between 2024 and 2025, as the academic and research interest in this field of personalised learning technologies has grown across the region, as seen in Figure 2. It was found that Panel A had the highest number of studies conducted in South Africa, Kenya, Ghana, Nigeria, Rwanda and Zambia, with several studies using a broader African or Sub-Saharan African perspective. The geographical distribution indicates that research into adaptive AI continues to be focused within countries where the digital infrastructure, research capacity and educational technology ecosystems are comparatively stronger [31], [32]. Also, the under-representation of numerous African states indicates a number of significant gaps in geography that need to be explored in future empirical studies.

The methodological diversity of the studies included in the present study is represented in Panel B. While case studies, conceptual papers and reviews made up a large share of the evidence base, fewer studies used rigorous longitudinal or large-scale experimental designs. This methodological approach aligns with the fledgling status of adaptive AI research in African education, where pilot studies for implementation are often followed by the evaluation of the technology at a broader scale [23], [27]. Despite the variety of research designs, the review is reinforced by the complementary empirical, theoretical, and policy lenses that together offer a broad understanding of the technological, pedagogical, and governance aspects of implementing adaptive AI.

This is also reflected in panel C, which shows that the most prevalent technological focus in the literature reviewed was Intelligent Tutoring Systems (ITS), adaptive learning platforms, and AI-driven personalised learning systems. The mobile AI tutor and AI-enabled educational robotics were also explored in more recent research and studies, and so was the use of generative AI applications, in which the technologies were becoming more flexible, learner-centred, and context-specific in their approach to education [8], [9], [14]. The diversity of the AI technologies also suggests that the technology is moving beyond experimental proof-of-concept systems to more classroom applications that can assist with personalised learning in varied learning environments.

The evidence map shows that AI in African education is a growing field, with a variety of studies and methods being explored. The 2013 Global Assessment revealed that the evidence base is relatively weak, however, because the majority of studies in this field are in relatively few countries, and are carried out as short-term implementation studies. Future studies should thus focus on multi-country joint efforts, longitudinal studies, and comparative analyses of under-represented regions to enhance the generalisability of the evidence and develop contextually tailored adaptive AI solutions for African education [5], [21].

III. Results and Findings

A. Evidence Distribution: A systematic review of 26 studies published from 2020 to March 2026 that covered research in South Africa, Kenya, Rwanda, Ghana, Nigeria, Zambia and the general Sub-Saharan African context. Of the studies presented in Table 5 and Figure 2, those in higher education were the most prevalent, followed by those in secondary education and then those in primary education, technical and vocational education and training (TVET). The studies included in this paper used a variety of study designs, such as quantitative, qualitative, mixed methods, case study, implementation, review and policy design, and the range of these studies gives a strong basis for assessing adaptive AI (AI) technologies in African education [8], [23], [27]. The technologies analysed included the intelligent tutoring systems (ITS), the adaptive learning platforms (ALPs), mobile AI tutors, AI learning companions, educational robotics, AI-based assessment systems, and generative AI applications. Intelligent tutoring and platforms for adaptive learning dominated the evidence base, and more recent studies looked at lightweight mobile AI solutions for resource-poor educational settings [9], [11], [14].

B. Educational outcomes: In all the studies reviewed, adaptive AI technologies had consistently positive education impacts on academic performance, student engagement, personalised learning and vocational skills. Several studies showed that the adaptive learning systems can provide personalised learning by continuously adapting learning pathways, content difficulty, and feedback based on learner performance [8], [15]. It was demonstrated in Kenya and Nigeria that mobile AI models could effectively be used in vocational education in low-resource settings. Mobile AI models could be effectively used in vocational education in low-resource settings, as demonstrated. The interventions reported increases in learning efficiency and task accuracy in the presence of limited computational resources [11], [12]. Likewise, the use of adaptive learning systems that give feedback in real-time and allow for progression based on competency levels was shown to positively impact learner motivation, participation in the classroom, and learning outcomes in Rwandan classrooms [9]. In higher education, a South African study and a Ghanaian study found intelligent tutoring systems to be associated with better personalised pacing, immediate corrective feedback, learner retention and learning experience. The adaptive systems alleviated learner failure risk, continually tracking student progress and offering personalised teaching assistance [8], [14], [32]. In all sectors of education included in the review, the selected studies consistently showed that adaptive AI tools benefited learning by providing pathways of personalization, adaptive feedback, and learner modelling, thus enabling more responsive teaching and learning.

C. Factors affecting adaptive AI implementation: While the positive educational outcomes were noted across the studies, there were also some barriers identified that had an impact on successful implementation. Key barriers mentioned most often were limited digital infrastructure, unreliable electricity supply, lack of internet connections, lack of access to digital devices, and affordability, especially in rural and under-resourced educational environments [11], [29], [31]. Sustainability of institutions was also a recurring issue. Some used donor support or pilot projects, but the concern is whether these can be sustained beyond the external funding source, as well as whether they are scalable and can be taken over by the institutions [12], [27]. In addition, several studies documented that having the technology was not sufficient and that there was a need for the right institutional infrastructure, strategic direction and continued investment in technology for digital education [21], [32]. One of the most commonly mentioned implementation enablers was teacher preparedness. Adaptive AI systems were consistently used as decision-support technologies and were integrated to support classroom-based learning and teaching by automating repetitive assessment tasks, providing adaptive feedback, and allowing teachers to focus on mentoring, facilitating, and higher-order pedagogical activities [14], [32]. Research also showed that professional development and ongoing teacher support have a significant impact on implementation success, compared to technology-first approaches [23], [27]. Ethical and governance issues were also extensively mentioned. Issues such as algorithmic bias due to training data that are not representative of Africa, inadequate data control and governance, privacy protection, transparency, and accountability mechanisms were common concerns [5], [21]. Some studies also highlighted the need for culturally responsive AI systems that can facilitate local curricula, indigenous languages, and pedagogical approaches that are locally appropriate, especially in multilingual African contexts [9], [17].

D. Quality appraisal results: Quality appraisal suggested that the methodological quality of the included studies was generally satisfactory. The majority of the studies had high-quality ratings, with 8-10 rating levels indicating clearly stated research goals, suitable methodological designs, clear analytical processes, and relevance to the implementation of adaptive AI in African education. Moderate quality ratings were assigned to a smaller number of studies (5-7) because of methodological reporting limitations, sample size, and implementation scope limitations. Relatively few studies were rated as low quality. Importantly, there was no exclusion of studies on the basis of quality appraisal alone, because implementation research, policy analyses, and conceptual studies were useful in providing context for the emerging field of this review. In the thematic synthesis process, however, methodological quality was used to inform the weighting of the evidence, so that conclusions were supported by the most methodologically sound studies found, but some implementation insights were also kept that were related to the themes [24], [26].

E. Cross pattern by evidence: The 26 studies included had several common themes. First, adaptive AI technologies have been consistently linked to increased learner engagement, personalised instruction, academic success, and competency building at various educational levels and in a variety of national settings. Second, the success of implementation always required an interplay of technological infrastructure, institutional preparedness, teacher capacity, and governance structures and not the AI technology itself. Third, research has grown significantly on culturally responsive, locally relevant and ethically sensitive adaptive AI systems that can respond to linguistic, infrastructural and socio-economic diversity that typifies African education systems. These recurring patterns provide the empirical foundation for the interpretive discussion presented in the subsequent section.

IV. DISCUSSION

Evidence from 26 synthesised studies across Africa shows that AAI tutors across Africa regularly and positively influence student achievement, engagement and workplace preparedness development, depending on contextual factors. This discussion is not just to repeat the findings but to explain these in the larger context of the use of adaptive AI in education in Africa. Evidence from multiple countries, educational levels and AI technologies is used to compare and contrast the themes identified, in order to explain how they converge to help us understand the opportunities and challenges of adaptive AI tutors.

A. Factors Explaining Disparities in Outcomes Across African Contexts

While educational outcomes were largely positive in the majority of studies included in this report, the size of the effect and consistency of the outcomes across countries, sectors and implementation contexts were variable. The disparities could be attributed in a significant part to the differences in digital infrastructure, institutional readiness, teacher preparedness, policy support and the maturity of AI implementation. The findings from the studies in relatively well-resourced Higher Education Institutions in SA and Ghana have been consistent and reported that the integration of an adaptive system into existing digital learning environments with a good ICT infrastructure and professional development of the staff was reported to improve academic performance and learner engagement [8], [14], [19][8]. The latter, on the other hand, has been found to yield positive results in lower resource settings only when deployed in a mobile-first approach, where the technology can run offline, and the computational models are simplified [11], [12], [26].

Mobile compatibility and low-bandwidth adaptive AI solutions were consistently found to be critical implementation barriers, and the available evidence supports a prioritization of these solutions due to the identified connectivity limitations, affordability problems, and limited access to digital devices in the included studies [11], [12], [29]. The findings are also corroborated by a wider regional analysis that highlights the need for readiness of infrastructure for sustainable incorporation of AI in educational settings in Africa [27], [31], [33]. The second argument, that offline capable adaptive AI systems enhance educational outcomes, however, still needs further empirical evidence as relatively few studies have directly examined fully offline adaptive learning environments, or compared offline and cloud-based adaptive learning systems in terms of their impact on educational outcomes [5], [30].

Likewise, culturally relevant, curriculum-aligned, and locally contextualised learning materials emerged as a recurring theme across the different papers, which was also found to be critical for equitable implementation of AI [17], [21]. Other studies emphasised the need for contextualizing adaptive AI with local learner contexts, socio-cultural contexts, and teacher practices, for enhancing the relevance and adoption of AI in education [9], [32]. However, there is limited direct evidence that compares indigenous-language adaptive AI models or culturally localized intelligent tutoring systems in the current literature in Africa. As such, these recommendations are drawn from both the empirical findings from experience and the theory-informed interpretation of how adaptive AI systems can be developed to enhance access, equity, and learning outcomes in various education contexts across Africa.

The results show that technological sophistication is not a decisive determinant of the success of implementation, but rather, the educational effectiveness is created when technological capability meets contextual readiness. There were also variations between educational levels. The institutions of higher education (IHEs) generally showed higher institutional capacity in the use of adaptive AI technologies due to high ICT infrastructure, high digital literacy, and well-developed e-learning ecosystems. On the other hand, teacher preparedness, curriculum alignment, learner accessibility, and community acceptance were more influential in implementing the program in primary and secondary education. The aspects of these contextual variations further emphasise the need to consider adaptive AI implementation as a socio-technical process, not just a technology innovation. the

A. PLATO and CLT underpinning discussion

The results are also discussed in terms of the integrated theoretical frame of PLATO and Constructivist Learning Theory.

The interpretation of these findings is done using the two theoretical frameworks of PLATO and CLT, to gain a better understanding of both the technological mechanisms and pedagogical processes underlying AI-supported personalised learning.

1) *PLATO*: The PLATO framework is an important theoretical explanation for the technological mechanisms that

underlie adaptive AI tutors. PLATO was first designed to account for the use of computer-assisted instruction, automated sequencing, learner modelling, continuous assessment, and immediate feedback, and thus provides a relevant frame of reference for understanding how modern adaptive AI systems are able to tailor learning experiences for individual learners [3], [14]. All the reviewed studies showed these technological features of adaptive AI tutors, which include real-time feedback, personalised learning paths, variable difficulty, and performance analysis. In essence, adaptive AI systems dynamically adjust teaching methods based on student performance, effectively making learning flexible and dynamic, as originally envisioned in PLATO. The review does, however, reveal that technology adaptation is not enough to ensure educational success. Being able to provide proper infrastructure, curriculum integration, institutional support, and teacher facilitation was the key to the effectiveness of the adaptive mechanisms of PLATO. Therefore, PLATO provides an understanding of the nature of adaptive AI systems for personalised learning, while not fully addressing the educational contexts in which learning outcomes vary.

2) *Constructivism and Pedagogical Processes*: While PLATO provides insights into the technological processes, CLT elucidates the pedagogical processes that impact engagement and learning outcomes. Constructivism focuses on the students as active constructors of knowledge and emphasises active interaction, reflection, and scaffolding in learning experiences. The evidence reviewed in this review clearly showed that adaptive AI tutors increased learner engagement through personalised pacing, competency-based progression, immediate feedback and learner autonomy [9, 10, 13, 15]. These results are very similar to the ideas of constructivism, as adaptive systems continually modify instructional support that is commensurate with the cognitive needs of learners as they change over time. The review also highlights the ongoing significance of teachers in a learning context with AI support. Adaptive AI did not replace teachers, but rather transformed their roles to become facilitators, mentors, formative assessors and higher-order support in teaching [16] and [17]. Teachers are thus placed at the heart of the process of understanding student needs, adapting AI suggestions to fit the context, and ensuring a rich interaction in their lessons. This discovery corroborates the current views of Constructivism that are associated with the concept of guided learning and the role of scaffolding by the teacher in the process of personalised learning.

3) *Integration of PLATO and Constructivism*: The best results come when technological intelligence (the automatic sequencing and feedback in PLATO) is used together with learner-centred pedagogy (the focus on autonomy and contextual engagement in Constructivism). Existing literature demonstrates that AI platforms can be used as an “instructor's exoskeleton,” in addition to their role as a facilitator of the higher-order facilitation [16], [17]. Technology-first rollout, as compared to deployments that deliberately situate teachers as facilitators, was more likely to see lasting improvements [5], [19]. The integration highlights the importance of the role of instructional design in fostering the effectiveness of AI, rather than technology itself.

4) *Governance, Infrastructure and localisation as moderating factors*: One of the most significant findings emerging from this review is that infrastructure readiness, ethical governance, and contextual localisation consistently moderated the effectiveness of adaptive AI implementation across African educational systems. Infrastructure barriers such as unreliable electricity, limited internet connectivity, digital devices and lack of technical support were also mentioned as a major obstacle to scaling beyond the pilot implementation [7], [34]. The results make it clear that technology innovations for educational benefits can only be achieved if institutional capacity is adequate. The studies reported concerns about data privacy, algorithmic bias, transparency, explainability and responsible AI governance [19], [20], [23]. Because many adaptive AI systems are trained on datasets originating outside African educational contexts, the potential for cultural bias and unequal learning experiences remains a significant concern. Consequently, responsible AI governance requires locally representative datasets, transparent decision-making processes, and appropriate regulatory frameworks. The effectiveness of implementation was further enhanced by cultural localisation. Research studies have shown across the board that adaptive AI systems had more impact when learning materials were culturally relevant to the local curriculum, indigenous languages, culturally relevant pedagogies, etc [9], [17], [35]. Localisation, therefore, functions not merely as a technical adaptation but as an essential educational requirement for equitable AI implementation.

5) *Policy Implications for Sustainable Adoption*: Technical thriftiness – mobile first and offline capable designs – need to be prioritised to ensure equitable reach in low resource environments [12]. Also, teacher preparedness is very crucial because the effectiveness of AI tutors depends on how teachers facilitate them; policies should invest in teacher preparedness to use AI in constructivist pedagogies [29]. To add on, ethics in governance is an urgent need to mitigate the risks of algorithmic bias, data privacy and cultural mismatch. It is important to note that local data sets, clear consent processes and content tailored to gender needs are important to avoid exclusion and inequity [36]. In addition, sustainability mechanisms need to be integrated into the policy, beyond short-term experiments and be scaled up to the systems level with reliable support from teacher investment, infrastructure, funding continuity and curriculum alignment [4], [19]. Lastly, there is a need to conduct longitudinal research to assess the long-term effects of AI on learner trajectories, career readiness and educational equity, since the majority of existing studies are short-term and fragmented [9], [37]. This Africa-centred synthesis focuses on

contextual factors, including infrastructure readiness, cultural localisation and teacher facilitation, which are important considerations not highlighted in other global systematic reviews of adaptive AI tutors and personalised learning that also emphasise the technological sophistication and algorithmic optimisation aspects of personalised learning[2], [22], [38], [39]. The novelty of the present review is the stark contrast between global studies that tend to assume stable digital ecosystems and Africa's implementations that demonstrate how digital ecosystems must adapt PLATO's sequencing logic and CLT's scaffolding principles to low-resource realities. The study, which places adaptive AI in various contexts across Africa, builds on the current literature and offers African-specific insights into equitable and sustainable adoption[23].

6) *Comparison with previous systematic reviews*: The findings of this review generally align with previous global systematic reviews that report positive relationships between adaptive AI technologies and learner engagement, personalised instruction, and academic performance [2], [22], [34]. However, unlike many international reviews that primarily emphasise algorithmic sophistication, learning analytics, and technological optimisation, the present review demonstrates that successful implementation within African educational systems depends equally upon contextual conditions, including teacher preparedness, infrastructure readiness, governance and cultural responsiveness. Whereas previous reviews frequently synthesised evidence across diverse global contexts, this Africa-centred synthesis reveals implementation challenges that are often underrepresented within international literature. These include unreliable electricity supply, resource-constrained learning environments, limited access to the internet, multilingual classrooms, and the need for culturally localised AI models. This review, therefore, adds to current research and spans the socio-technical environments in which adaptive AI technologies are being implemented.

7) *Strengths and limitations of the evidence*: The findings from this review offer promising support for the educational value of adaptive AI tutors in educational settings in Africa. Empirical studies, mixed-methods investigations, implementation studies, systematic reviews and policy analyses allowed for an overview of the technological, pedagogical, organisational and governance dimensions. In addition, PRISMA was applied alongside SPAR-4-SLR to enhance methodological transparency and reproducibility. However, this evidence is limited in scope and is subject to a number of limitations. The majority of the studies included were small or of short duration or involved the analysis of a single institution and thus the reported results are not widely generalisable. There are limited evaluations that take a longitudinal approach to look at sustained learner achievement, institutional transformation, and long-term educational equity. Considerable heterogeneity in study designs, outcome measures and AI technologies also prevented quantitative meta-analysis. Thus, while the general findings are uniformly positive for the educational potential of adaptive AI tutors, the results of the longer-term and larger-scale studies should be taken with a grain of salt until further research backs them up in the context of multiple countries.

B. *Proposed Conceptual Framework for Adaptive AI Tutors in African Classrooms*

Through the systematic synthesis of the studies included, the authors found that various factors related to technology, pedagogy, institutions and infrastructure, ethics and context are important to the successful implementation of adaptive AI tutors in African classrooms. These factors do not exist in isolation, but are interdependent, influencing learner engagement, personalised learning experiences and educational outcomes. Gathered from these regularities that appeared in the literature examined in this study, the Integrated Conceptual Framework for Adaptive AI Tutors in African Classrooms is proposed. The framework is the main product of this study, bringing together the scattered evidence to provide a coherent socio-technical model of how adaptive AI can facilitate equitable and contextually appropriate education in different learning environments in Africa.

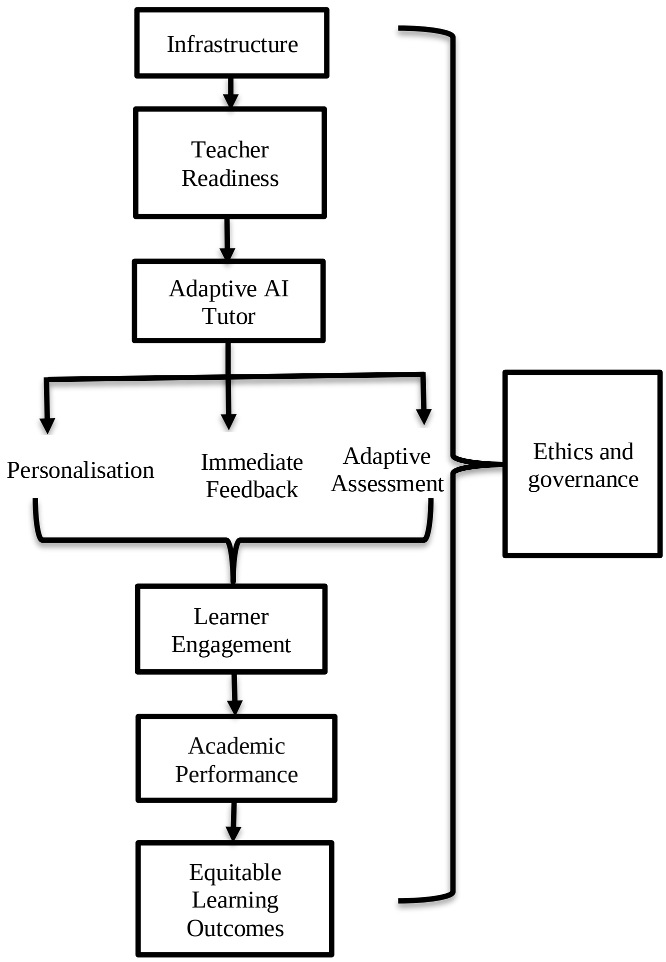

Figure 3. Integrated framework for Adaptive AI Tutors in African Classroom.

The findings of this systematic review were presented in a conceptual framework integrated and summarised into one figure (Figure 3). The framework suggests that adaptive AI tutors can start to be successful if the following national and institutional conditions are established. National AI policies, ethical governance and regulatory frameworks set the context for the strategic environment in which educational institutions work. Operational capacity for implementing AI is provided by institutional readiness, defined as leadership commitment, ICT infrastructure, funding, digital policy and technical support[5], [8], [19].

In this institutional context, teacher readiness is the most important pedagogical facilitator. All relevant studies agree that teachers need to have a certain level of expertise with AI, a proficiency in pedagogy and ongoing professional development to successfully implement adaptive AI into their classrooms. Thus, teacher preparedness serves as a mediator between the availability of technology and its meaningful use in education[16], [17], [40].

The adaptive AI tutor is the technological backbone of the framework. All of these studies identified three key attributes of successful systems: adaptive learning paths that support the variability of learners, adaptive feedback that gives learners immediate instruction and adaptive assessment that continually adapts learning activities to learner performance [14], [28], [29].

These adaptive functions as a whole contribute to the engagement of learners by enhancing participation, motivation and interaction with learning activities. In line with the principles of Constructivist Learning theory, engagement is enhanced by providing individual learning experiences that require active building of knowledge instead of passive sharing of content [9], [10], [15].

The framework suggests that a continuous process of engagement of learners in learning leads to better learning outcomes, such as higher academic performance, better learner motivation, better self-regulated learning skills, better digital competence and better equitable educational opportunities. This finding was noted in various studies conducted in different contexts of education across Africa [8], [11], [13].

Lastly, the framework outlines cross-cutting principles of responsible AI governance, data privacy, algorithmic fairness, explainability, cultural responsiveness, indigenous language support, accessibility and sustainability, which will have an impact on each stage of implementation[7], [23]. These elements do not stand in isolation, but work in tandem to uphold the ethical, contextual and educational integrity of adaptive AI tutors in African classrooms.

8) *Theoretical interpretation of the proposed framework*: The proposed framework is theoretically grounded on the complementary views of PLATO and Constructivist Learning Theory. PLATO explains the adaptive technological mechanisms that enable the personalisation of the delivery of instruction, the provision of intelligent feedback and the adaptation of learning pathways as a function of the learner's performance. These adaptive responses are understood via the constructivist perspective of how they enable meaningful engagement with customised learning experiences, thereby supporting active knowledge construction. Combining these theoretical frameworks shows that adaptation via AI is not just a matter of technology but a product of intelligent adaptive systems, pedagogy focused on the learner and supportive learning environments. The framework, therefore, enriches the current theoretical knowledge as it considers adaptive AI in African classrooms as a socio-technical process that includes technological, pedagogical, organisational and governance aspects across multiple countries.

C. Limitations

The review has some limitations that must be taken into account when interpreting the findings: First, the review only included the databases and additional citation search methods described in the methodology. This may mean that relevant publications in local journals, institutional repositories, conference proceedings, government documents or in non-indexed African journals have not been captured. This constraint is significant as research from institutions with fewer publications and indexing may be underrepresented. Secondly, the publication bias could have been the successful and innovative AI interventions, with unsuccessful, discontinued, or null-result projects not being published. The recommendations on mobile compatibility, offline operation, cultural localisation and teacher facilitation are thus supported by a strong body of evidence. Still, they are not necessarily supported by a comparative or longitudinal design. Third, despite a methodological quality appraisal performed in a structured manner, methodological heterogeneity of the evidence base is still substantial, with quantitative, qualitative, mixed-method, implementation studies, conceptual studies and policy studies. Thus, although the review-specific appraisal framework helped to ensure a consistent evaluation of the different study designs, caution needs to be taken when comparing the methods used in different studies directly. In addition, given that the field of adaptive AI in education in Africa is still in its early stages of development, there were relatively few large–scale (longitudinal or experimental) research studies available, which creates a need for further detailed empirical studies in the future.

V. CONCLUSION

This systematic literature review shows the great promise of AAI tutors in revolutionising education in the Sub-Saharan Africa region, by improving academic outcomes, speeding up vocational skill learning and supporting learners' engagement through customised learning paths and real-time feedback. The experiences of Nigeria, Rwanda, South Africa, Kenya, Ghana and Zambia show that AI systems can be technically thrifty, pedagogically aligned and culturally responsive and can yield measurable results. When viewed from the two perspectives (PLATO) and (CLT), these results highlight the co-production of the efficacy of AI in education, which is shaped by both algorithmic sophistication and learner-centred pedagogy. However, there are ongoing challenges, such as infrastructural limitations, algorithmic bias, sustainability concerns and data privacy issues, indicating that the power of technology cannot ensure equity. The policy frameworks need to therefore go beyond aspirational ethics to operationalise notions of fairness, transparency and accountability in the classroom contexts and incorporate notions of African values, including Ubuntu and culturally localised data sets, including gender responsive data. It should focus on the following aspects to facilitate equitable AI adoption: mobile-first deployments, teacher professional development and culturally localised approaches.

Services need to be designed to be mobile-first and offline capable, teacher professional learning must be supported and there must be robust governance and longitudinal studies to inform the long-term impacts of learning on learner pathways and equity in order to be successfully adopted. Finally, in the future, AAI tutors should be seen as a support for the formative assessment and for learners in the future, rather than a replacement for teachers, as an exoskeleton for the teacher. The convergence of technological expertise, pedagogical and ethical precautions can help with the way forward for inclusive, human-centred and sustainable educational transformation in Sub-Saharan Africa through leveraging AI. From a practical perspective, findings indicate that primary school curricula need to incorporate AI literacy, using scaffolded units that integrate unplugged computational thinking with mobile AI tutors. This is a two-way strategy to ensure inclusivity in a variety of infrastructural realities.

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