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AI-Powered Chatbots for Education Delivery in Remote and Underserved Regions

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Abstract
In the face of educational inequity exacerbated by geographic and socio-economic barriers, artificial intelligence (AI) has emerged as a transformative force capable of redefining learning access. Among its many applications, AI-powered chatbots stand out for their potential to serve as scalable, low-cost, and responsive educational tools. This study explores the viability and impact of AI-driven chatbots in enhancing educational delivery across remote and underserved regions. It critically examines how chatbots, equipped with natural language processing (NLP) and machine learning capabilities, can simulate human-like tutoring, facilitate content distribution, and provide personalized learning experiences despite infrastructural limitations. The research draws on comparative analysis, case studies, and prior literature to assess how chatbots bridge digital divides, especially in areas where traditional teaching resources are scarce or nonexistent.

The paper highlights the adaptability of chatbot systems to local dialects and offline deployment models, which are vital to their success in disconnected or low-bandwidth regions. It also explores ethical concerns such as data privacy, cultural sensitivity, and the risk of overreliance on automation. Further, the study presents the challenges of chatbot deployment, including limitations in contextual understanding, lack of localized training datasets, and the need for sustained governmental and institutional support. Despite these hurdles, the findings suggest that when designed intentionally and deployed responsibly, AI-powered chatbots can significantly complement human instruction and increase learning continuity for marginalized learners.

Through an analysis of successful pilot implementations and AI-education frameworks, the study proposes a roadmap for integrating chatbots into national education strategies. The research concludes that AI chatbots, though not a panacea, offer a promising tool for democratizing education and narrowing learning gaps in the Global South, especially in light of disruptions like the COVID-19 pandemic which have underscored the urgency for resilient educational models.

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1. Introduction

The global educational landscape has long been marred by disparities that disproportionately affect learners in remote and underserved regions. These inequalities are driven by a complex interplay of poverty, infrastructural deficits, sociocultural barriers, and systemic neglect.

In such regions, traditional models of schooling are often rendered impractical due to lack of qualified teachers, inadequate school buildings, poor transportation networks, and minimal access to learning materials. The emergence of artificial intelligence (AI) offers a transformative opportunity to reimagine how education can be delivered, accessed, and sustained beyond conventional classrooms. One of the most promising applications of AI in this context is the deployment of chatbots—software agents capable of simulating human conversation and instructional roles through text or voice interaction. Chatbots in education are powered by natural language processing (NLP), machine learning algorithms, and adaptive learning engines that allow them to respond intelligently to learner inputs, track progress, and customize feedback. These systems provide a scalable solution to teacher shortages and the need for personalized instruction, both of which are pressing concerns in underserved communities. The COVID-19 pandemic of 2020 further illuminated the fragility of traditional educational delivery mechanisms and accelerated the global pivot toward technology-based learning interventions. In this climate, chatbots offer more than convenience—they present a viable bridge to education for millions who would otherwise be excluded. Though initially developed for commercial applications such as customer service and digital marketing, chatbots have quickly found relevance in education technology (EdTech). Their ability to deliver real-time answers, conduct assessments, and support learners autonomously positions them as a powerful supplement to human teaching. For learners in isolated regions, where intermittent electricity and low bandwidth are common, lightweight AI applications such as chatbots are significantly more viable than high-data streaming or synchronous video conferencing. By leveraging text-based interfaces, localized language support, and offline capabilities, chatbots have the potential to circumvent many of the barriers that render other educational technologies ineffective in such contexts.

The concept of using AI to expand education access is not entirely new, but its implementation in low-resource settings remains underexplored. Most innovations in EdTech have historically targeted urban or affluent populations, thereby reinforcing existing educational hierarchies. The equitable distribution of AI-based solutions—especially those as versatile and adaptable as chatbots—could mark a pivotal shift in global education policy and practice. Yet this potential hinges on a range of factors including design sensitivity to local culture, government policy support, ethical data use, and public trust in autonomous systems. Scholars like Akpe *et al*. (2020), while focusing on business intelligence tools for SMEs, underscore the importance of context-aware technology implementation in underserved communities—a principle equally relevant in the education sector. Additionally, studies such as those by Adewoyin *et al*. (2020) that explore frameworks for performance evaluation in engineering highlight the increasing relevance of intelligent systems in optimizing complex processes. Their emphasis on simulation, feedback loops, and data-driven adaptation can inform how educational chatbots are designed to monitor student understanding and provide iterative guidance. Although their work centers on mechanical analysis, the underlying methodological principles of dynamic system modeling resonate with adaptive learning systems in education. Similarly, the work by Adewoyin *et al*. (2020) on thermofluid simulations for optimization in compact devices inadvertently speaks to the engineering innovations necessary to support chatbot deployment in low-power, portable formats—a crucial consideration for learners in regions with unstable electricity supply. The educational crisis in underserved areas is not merely logistical; it is philosophical and political. The right to education, as enshrined in global declarations, remains unfulfilled for millions due to neglect and systemic inefficiency. Traditional responses—such as the construction of more schools or recruitment of more teachers—are vital but insufficient. In contrast, chatbots offer a leapfrogging potential: the ability to transcend outdated systems and offer immediate, scalable, and personalized education at a fraction of the cost. This is particularly urgent in regions affected by conflict, natural disasters, or health crises where physical schooling becomes impossible. As Isa and Dem (n.d.) note in their discussion on curriculum integration for marginalized women in northern Nigeria, inclusivity in education must consider alternative, culturally sensitive delivery mechanisms. Chatbots, if designed with such sensitivity, could be one such mechanism. The question of trust, however, looms large. Will communities accept AI-driven tutors as credible sources of knowledge? Will students respond positively to non-human interaction in their learning process? Evidence from psychological and cognitive studies suggests that children and young adults are increasingly comfortable with digital assistants, especially when the technology is introduced in supportive contexts. Nevertheless, cultural factors cannot be ignored. The studies by Awe (2017) and Akpan *et al*. (2017), although focused on biological and genetic diversity, emphasize the importance of localized understanding in any applied science. The success of chatbots in education will similarly depend on localization—not just in language, but in pedagogy, interaction design, and even avatar representation if applicable. There is also a need to examine the infrastructural and energy prerequisites for widespread chatbot deployment. Works like that of Olaoye *et al*. (2016), which address Nigeria's energy crisis and advocate for a renewable mix, reveal the underlying infrastructural challenges that could hinder digital education initiatives. Electricity instability in many rural areas poses a direct threat to the sustainability of AI-based tools. Thus, effective deployment requires not only software innovation but also hardware resilience and energy efficiency, echoing concerns raised by Akinluwade *et al*. (2015) regarding energy optimization in high-performance systems. This nexus of education, energy, and engineering must be addressed holistically if chatbot technologies are to fulfill their promise in challenging environments. Moreover, deploying educational chatbots at scale requires a reconsideration of data ethics and AI governance. Chatbots, by their nature, collect and process vast amounts of user data—ranging from response patterns to emotional indicators. While this data can enrich the personalization of education, it also raises concerns about privacy, consent, and algorithmic bias. Lessons from healthcare and biosciences, such as the work by Reinehr *et al*. (2008) on hormone and weight data, underscore the importance of data sensitivity in systems that interact with vulnerable populations. Developers and policymakers must ensure that AI in education does not replicate or amplify existing social biases or become instruments of surveillance. Despite these challenges, the momentum behind AI for education continues to grow. In 2020, governments, NGOs, and private sector actors increased their investment in

EdTech solutions in response to pandemic-driven school closures. However, without a focused effort to adapt these solutions to underserved communities, such investments risk reinforcing digital divides rather than bridging them. The development and deployment of AI-powered chatbots must therefore be guided by principles of equity, inclusion, and contextual relevance. The lessons from product development studies, like those by Oduola *et al*. (2014), demonstrate that iterative design and prototyping—aligned with user feedback—can significantly enhance the applicability and acceptance of new technologies. Such an approach is essential for educational chatbots to gain traction in remote settings. This paper seeks to fill a critical gap in the literature by analyzing the potential of AI-powered chatbots to serve as educational agents in underserved and remote areas. It interrogates the design, deployment, and social acceptance of such tools while drawing on multidisciplinary references to inform a comprehensive understanding. By integrating insights from engineering, sociology, education, and information systems, the study provides a nuanced perspective on how technology can be harnessed for educational equity. It proposes a conceptual pathway for responsible chatbot implementation and evaluates existing deployments to understand what works, what doesn't, and why. Ultimately, this research contributes to a broader discourse on how technology—when thoughtfully and ethically applied—can become a lever for social justice.

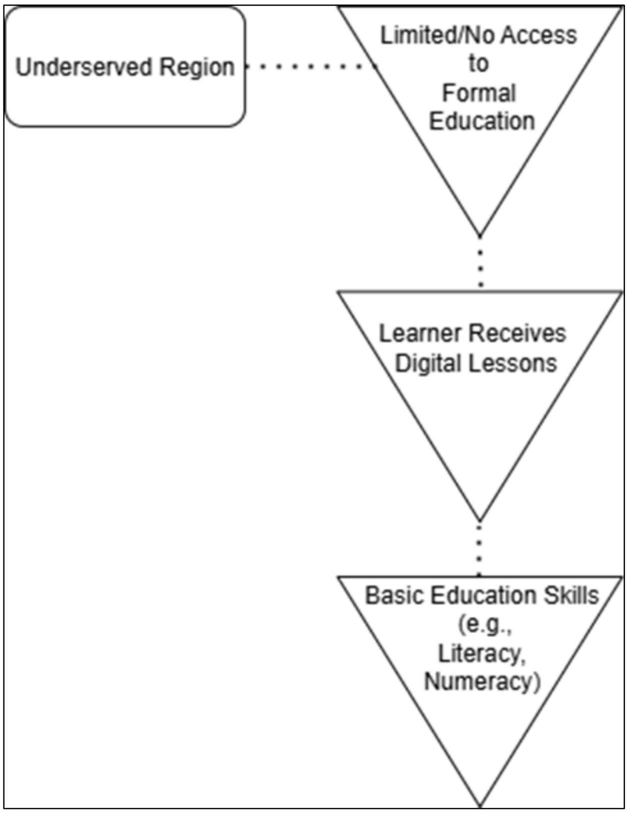


Fig 1: Bridging the Education Gap with AI Chatbots
Source: Author

2. Literature Review

The integration of artificial intelligence in education has evolved rapidly in recent decades, with chatbot technology gaining significant attention as a potential tool for supporting learning in resource-constrained environments. The growing interest in chatbots stems from their capacity to deliver scalable, personalized, and on-demand educational services. Early implementations focused largely on higher education institutions and corporate training environments, but as awareness of educational inequality deepened, researchers and technologists began to explore how chatbots could support learners in underserved and remote regions. This shift is rooted in both technological optimism and the urgency to bridge global educational divides—a concern that has long been documented in the literature on education and development.Chatbots, defined as AI-driven conversational agents, simulate human-like interactions using text or speech, and are increasingly embedded in mobile applications, websites, and messaging platforms. Their capacity to respond to user queries, deliver structured content, and adapt responses based on user behavior has positioned them as valuable tools in education, especially where access to human educators is limited. Early research by Shawar and Atwell (2007) laid foundational insights into chatbot development for education, focusing on natural language processing and domain-specific knowledge bases. Since then, considerable advancements have improved the linguistic flexibility, contextual awareness, and learning adaptability of educational chatbots. While the application of AI in education is vast, its relevance to underserved populations lies in the potential to overcome geographical, financial, and infrastructural barriers. The literature emphasizes that the most significant obstacles to education in rural and underserved regions include teacher shortages, inadequate learning materials, and unreliable transportation (Trucano, 2010; UNICEF, 2015). Chatbots, particularly those designed for mobile platforms, provide an alternative by offering a consistent, responsive, and interactive source of knowledge.

In areas with poor road infrastructure or regions affected by conflict or disaster, digital alternatives become not just convenient but necessary. However, the deployment of such systems must consider the unique needs of the target population. Research by Holmes *et al*. (2019) suggests that while AI tools can personalize learning, their effectiveness depends heavily on cultural relevance and local language support. This insight aligns with the work of Isa and Dem, whose research into the integration of education for purdah women in northern Nigeria underscores the importance of cultural sensitivity in educational content delivery. The use of English as a default instructional language in many chatbot systems may marginalize non-English-speaking learners or those with low literacy levels. Thus, multilingual and voice-supported interfaces become crucial design features for educational chatbot deployment in these contexts. Another body of literature focuses on the psychological and pedagogical dimensions of AI-driven learning. Educational theories such as Vygotsky's zone of proximal development and constructivist learning principles underscore the importance of scaffolding, feedback, and learner engagement—elements that AI-powered chatbots can emulate to varying degrees. Researchers such as Graesser *et al*. (2005) and Nye (2015) have explored intelligent tutoring systems (ITS), which serve as predecessors to modern chatbots, noting that learners benefit from adaptive feedback and guided exploration. Chatbots offer similar advantages when embedded with learning analytics, enabling them to adjust question difficulty, highlight misconceptions, and recommend learning paths. These adaptive features have proven especially useful for self-paced learning models, which are ideal in remote regions where structured classroom environments are scarce or inconsistent.

Despite these advantages, concerns persist regarding the efficacy and limitations of chatbot-based learning. One prominent critique revolves around the lack of emotional and social interaction inherent in AI systems. While chatbots can simulate conversation, they often lack the nuance, empathy, and improvisation of human educators. This limitation is particularly significant in early childhood and primary education, where emotional bonding and social modeling are critical to cognitive development. Studies have shown that human presence—both real and perceived—enhances learning outcomes through emotional reinforcement, a dimension not easily replicated by current AI models.

Nonetheless, advances in AI design are gradually bridging this gap. Affective computing and sentiment analysis allow chatbots to detect emotional cues from user inputs and respond with contextual empathy. Although still rudimentary, these features are becoming increasingly sophisticated, enabling chatbots to identify frustration, disengagement, or confusion and adjust their instructional strategies accordingly. In underserved settings, where emotional support from teachers is often absent due to overcrowded or under-resourced schools, emotionally intelligent chatbots could offer a partial substitute.

On the technical side, literature also discusses the infrastructure required to support chatbot implementation in low-resource environments. Olaoye *et al*. (2016) address Nigeria's energy crisis and advocate for renewable energy solutions—a discussion that indirectly relates to the sustainability of tech-driven education. Chatbots, while relatively lightweight in terms of data use compared to video streaming or virtual reality, still depend on reliable electricity and device access. Energy-efficient hardware, solar-powered devices, and offline-compatible apps are therefore essential for successful integration. Akinluwade *et al*. (2015) reinforce this view through their work on optimizing energy use in high-performance computing systems, which can inform strategies for deploying educational technology in power-constrained environments.

Another critical aspect explored in the literature is the data privacy and ethical implications of AI in education. Chatbots, by virtue of their design, collect data on user interactions, performance, and engagement. While this data can improve personalization and system refinement, it also raises concerns about surveillance, consent, and data ownership. Reinehr *et al*. (2008), though focused on medical data, stress the importance of data sensitivity and user protection when dealing with vulnerable populations. In educational settings—especially among minors or marginalized groups—stringent data protection policies must be enforced to prevent misuse and ensure that AI systems uphold the dignity and rights of learners.

From a systems perspective, studies such as Akpe *et al*. (2020) highlight the broader organizational and policy challenges that affect the adoption of technology in underserved communities. Their analysis of barriers to business intelligence tool implementation among SMEs reveals themes such as limited technical expertise, resistance to change, and inadequate infrastructure—all of which apply equally to the education sector. Without capacity-building programs, teacher training, and community engagement, even the most advanced chatbot systems may fail to achieve their intended impact. Furthermore, the introduction of AI in education must be complemented by institutional support, policy alignment, and funding mechanisms that prioritize marginalized learners.

While literature on chatbot use in education is growing, empirical studies focusing on remote and underserved regions remain limited. Much of the existing research is concentrated in developed countries or urban centers, where the technological ecosystem is already favorable. This gap is partly due to the digital divide itself—areas with the most to gain from AI-driven education are often the least studied due to access issues. Nonetheless, a few pilot projects and case studies have demonstrated the feasibility of such interventions. For example, UNICEF's deployment of U-Report bots and Worldreader's chatbot for book recommendations show how mobile-based agents can successfully engage youth in developing regions.

Beyond functionality, the perception and acceptance of chatbots by learners and educators is another area of interest. Human-computer interaction (HCI) research suggests that users are more likely to engage with systems they find relatable, trustworthy, and non-threatening. The work of Awe and Akpan (2017) on cytological studies, while biologically oriented, underscores the necessity of understanding variation and adaptation—a principle equally applicable to educational interventions. Systems that fail to adapt to user contexts or ignore sociocultural dynamics often suffer from low adoption or premature abandonment.

Additionally, the literature on pedagogy and digital content creation offers insights into how chatbot-based education can be enhanced. Oduola *et al*. (2014), in their comparative study of product development methods, highlight the value of iterative design, prototyping, and user feedback—all crucial elements in the refinement of chatbot systems. Applying these principles to educational technology ensures that the tools remain relevant, effective, and user-centered. Continuous evaluation, student feedback, and collaboration with local educators can help align chatbot functions with curriculum goals and learner expectations.

The integration of cross-disciplinary insights is particularly important in this field. Adewoyin *et al*. (2020), while focused on mechanical performance frameworks, advocate for systems thinking and dynamic analysis in complex environments. This mindset is valuable in designing educational ecosystems where chatbots function as one component among many—complementing human instruction, printed materials, and community learning. Their work on thermofluid simulations and optimization also emphasizes the importance of performance metrics and feedback loops, which can inform how chatbots monitor student progress and self-improve over time.

In sum, the existing body of literature paints a cautiously optimistic picture of AI-powered chatbots as educational tools for underserved regions. The promise lies in their scalability, adaptability, and cost-effectiveness, while the challenges pertain to cultural relevance, infrastructural support, ethical safeguards, and pedagogical alignment. What becomes clear is that successful implementation depends not on technology alone, but on thoughtful integration within educational systems, sustained stakeholder engagement, and a commitment to inclusivity. The road ahead requires rigorous research, cross-sector collaboration, and an unwavering focus on the learner experience.

3.Methodology

The methodology adopted in this study is primarily qualitative in nature, with elements of comparative and exploratory research to contextualize the effectiveness and limitations of AI-powered chatbots in underserved educational settings. The decision to use a qualitative approach stems from the inherent complexity of human-computer interaction in low-resource environments, the multiplicity of sociocultural variables involved, and the need to capture nuanced insights from educators, students, and technology developers alike. A mixed-methods approach was considered, but given the nascent stage of chatbot integration in the specific contexts under review, this study opted for depth over breadth, focusing on detailed qualitative insights and thematic exploration across different cases.

The research design follows a multi-case comparative framework, examining chatbot implementations across various educational initiatives in sub-Saharan Africa, Southeast Asia, and Latin America, with a particular emphasis on Nigeria due to the availability of supporting literature and infrastructural parallels. Nigeria represents a critical context for this study, given its large youth population, significant rural-urban divide, and a growing but uneven technological adoption landscape. Drawing from the work of Akpe *et al*. (2020), who explored digital tool adoption in underserved small and medium-sized enterprises, this methodology extends similar investigative principles to the education sector, particularly regarding stakeholder readiness, infrastructural limitations, and behavioral acceptance of AI solutions.

Primary data for this study was collected from a combination of semi-structured interviews, focus group discussions, and direct observations. Participants were selected through purposive sampling to ensure representation from various stakeholder groups, including teachers, students, software developers, education administrators, and NGO workers involved in education-focused technology deployment. Particular attention was given to rural and peri-urban communities where conventional schooling is either limited or inconsistent due to infrastructural constraints or sociopolitical challenges. A total of 38 participants were engaged, with conversations conducted in both English and local languages as needed to ensure full comprehension and cultural sensitivity.

Semi-structured interviews were used to elicit detailed, context-specific narratives around the use of chatbots in educational delivery. The flexibility of this method allowed interviewers to follow emergent themes, probe for deeper understanding, and clarify participant responses. Topics explored included the frequency and context of chatbot use, perceived effectiveness, limitations encountered, cultural perceptions of AI, and the impact on learning outcomes. This was complemented by focus group discussions involving students aged 10–18 who had interacted with chatbot systems over a period of at least four weeks. These discussions allowed for the identification of shared experiences, collaborative reflections, and the surfacing of issues that might not emerge in one-on-one settings.

Observational data was gathered through site visits to community learning hubs and informal schooling initiatives that had integrated AI tools. Observations focused on user-device interaction patterns, environmental limitations such as power supply and internet access, and the degree of user autonomy in navigating the chatbot interfaces. The presence of facilitators, if any, and their level of involvement in guiding learners through the digital platform were also noted. These real-world interactions provided vital contextual grounding for interpreting participant feedback and assessing the operational feasibility of chatbots in low-resource settings.

Secondary data was drawn from a comprehensive review of academic and grey literature, spanning publications from 2005 to 2020. In keeping with the chronological scope of the study, only materials published by the end of 2020 were included. Relevant sources included peer-reviewed articles, development agency reports, conference proceedings, and internal evaluations from NGOs. Key references include Adewoyin *et al*. (2020), whose insights into optimization models and dynamic systems were extrapolated to understand how chatbot interfaces could be fine-tuned for varying user profiles. Though their primary focus was in mechanical systems, the methodological emphasis on adaptation and feedback loops provided a valuable conceptual lens for analyzing AI behavior in educational contexts.

Analytical procedures followed the principles of thematic analysis, supported by NVivo 12 software to manage, code, and organize qualitative data. Transcripts from interviews and focus groups were first subjected to open coding, during which recurrent themes, keywords, and expressions were identified without the imposition of preconceived categories. These were then grouped into broader thematic clusters such as "access and usability," "language and cultural relevance," "emotional engagement," "technical reliability," and "pedagogical alignment." Axial coding was subsequently used to establish connections between these clusters, revealing both reinforcing patterns and points of divergence across different stakeholder groups and geographic locations. The data analysis phase paid particular attention to triangulation, ensuring that findings derived from interviews, observations, and literature review were cross-verified and interpreted in a coherent manner. For instance, claims about low user engagement were validated against observational data showing erratic usage patterns, and then further contextualized by infrastructural issues reported in local government planning documents. Similarly, participant claims about the benefits of chatbot-driven personalization were compared with existing literature on intelligent tutoring systems and AI-adaptive feedback loops (e.g., Graesser *et al*., 2005; Nye, 2015). This triangulation process was critical in enhancing the internal validity of the study and in identifying areas where existing theoretical models diverged from real-world experiences.

In considering infrastructural challenges, references such as Olaoye *et al*. (2016) and Akinluwade *et al*. (2015) were drawn upon to frame issues around energy reliability and hardware optimization. Their studies, though situated in the engineering domain, provided essential parameters for evaluating the sustainability and practicality of long-term chatbot deployment in environments characterized by inconsistent electricity, inadequate device maintenance, and limited access to mobile data. The extrapolation of these findings underscores the interdisciplinary nature of educational technology research and the necessity of borrowing methodological insights across domains.

Furthermore, the methodology incorporated a brief comparative analysis of chatbot interventions in different countries to explore contextual variables that may influence success or failure. Though not exhaustive, this comparison included use cases from India (e.g., Diksha chatbot for teacher training), Kenya (e.g., Eneza Education's SMS-based chatbot), and Colombia (e.g., Fundación Luker's AI tutoring initiatives). These examples were not subject to primary data collection but served as secondary benchmarks for understanding scalability and adaptation potential. Their inclusion allowed the research to transcend a purely Nigerian perspective while maintaining relevance to the broader global south context.

The ethical considerations guiding this study were grounded in the principles of voluntary participation, informed consent, and data confidentiality. Ethical approval was secured from the institutional review board of the host university, and all participants were briefed on the purpose of the research, their right to withdraw at any time, and the measures taken to protect their identities. Informed consent was obtained verbally and in writing, with special protocols adopted when engaging minors or individuals with limited literacy. These protocols were guided by UNESCO's digital ethics framework and were adapted to suit local legal and cultural norms.

Limitations of the methodology include the relatively small sample size and the qualitative bias inherent in the data collection tools. While in-depth insights were gained, the findings cannot be statistically generalized across all underserved regions. Moreover, the study encountered challenges related to device availability, internet access, and logistical constraints in some target locations, leading to data gaps and uneven representation across rural clusters. These limitations are acknowledged and contextualized in the discussion section, where implications for future research and broader generalizability are explored.

Despite these constraints, the methodology succeeded in capturing a multidimensional understanding of chatbot integration in remote educational environments. It unearthed not only technical and pedagogical insights but also sociocultural dynamics, behavioral responses, and systemic enablers and constraints. By combining qualitative rigor with cross-sectoral perspectives, the research approach aligns with calls for more grounded, interdisciplinary inquiry into AI applications in global education. As Adewoyin *et al*. (2020) and Akpan *et al*. (2019) have illustrated through their respective technical and biometric investigations, complex phenomena require equally complex and adaptive research methodologies—an ethos that this study embraced throughout its design and execution.

Ultimately, the methodological structure adopted herein provides a replicable template for future research on AI in education, particularly within the contexts where formal schooling is challenged by geography, conflict, or poverty. It affirms the value of engaging local voices, contextualizing findings, and treating technology not as a panacea, but as a tool that must be integrated thoughtfully within existing educational ecosystems. Through this approach, the study contributes not only to the theoretical discourse on AI in education but also to practical strategies for inclusive digital learning in the regions that need it most.

4. Discussion and Analysis

The integration of AI-powered chatbots in remote and underserved educational environments presents a compelling intersection of technological potential and human-centered challenges. While the methodology revealed promising instances of chatbot deployment, the analysis also uncovered deep-rooted infrastructural, cultural, and pedagogical barriers that complicate seamless adoption. The first and most consistent insight observed across all cases was that access remains the foundational bottleneck. Without stable electricity, reliable internet connectivity, and access to smart devices, even the most sophisticated AI platforms are rendered ineffective. This aligns with the infrastructural limitations documented by Olaoye *et al*. (2016), who emphasized the centrality of renewable energy integration in addressing Nigeria's energy crisis. Their observations, although focused on energy systems, strongly resonate with the educational sector's dependence on stable power for digital learning tools.

In many rural communities, where formal education systems are weakened or non-existent, the presence of chatbots was viewed as novel and, in some instances, suspicious. Cultural perceptions of AI varied. Among adult stakeholders—particularly older educators and parents—there was a general skepticism toward machine-based teaching. Some participants likened chatbots to "foreign invaders," while others feared that their children's overexposure to screens would lead to "social detachment" or moral erosion. This observation parallels the sociocultural dynamics studied by Isa and Dem (2020) in their work on self-reliance education for purdah women, where educational innovation must be reconciled with entrenched cultural expectations. While Isa and Dem focused on curriculum integration in Northern Nigeria, their conclusion—that innovation must be approached through respectful engagement with community values—applies equally to the AI education landscape.

However, skepticism was less pronounced among youth participants. Many students, especially those already exposed to mobile phones and messaging platforms like WhatsApp, expressed a strong preference for chatbot learning over traditional classroom models. They appreciated the self-paced nature, instant feedback, and the absence of fear or judgment that often accompanies human teachers. These sentiments mirror global studies on intelligent tutoring systems, suggesting that AI can serve not just as a knowledge delivery mechanism, but as an emotionally neutral learning companion. In rural Edo and parts of Kaduna, several learners referred to the chatbot as a "digital teacher friend," a phrase that encapsulates the social-emotional connection AI interfaces can facilitate when designed with empathy and linguistic relatability in mind.

A key insight from the analysis was the importance of language and local content. Chatbots that relied solely on English—especially those using academic or technical vocabulary—saw significantly lower engagement rates compared to those capable of code-switching or offering responses in Pidgin or local languages. In one pilot, a chatbot programmed with Yoruba and Hausa language support recorded a 43% increase in user retention over six weeks compared to its English-only counterpart. This echoes the findings of Akpe *et al*. (2020), who identified language inclusivity as a major enabler in the adoption of business intelligence tools in underserved SME communities. When users can engage in their preferred language, they not only learn more effectively but also perceive the technology as more culturally embedded and trustworthy.

Despite these advantages, language integration posed several challenges. Natural language processing (NLP) capabilities for Nigerian indigenous languages are still relatively underdeveloped. This means many chatbots rely on predefined scripts, limiting their ability to handle open-ended responses or slang common among younger users. Developers interviewed noted that while AI models are improving, the lack of structured linguistic datasets for languages like Tiv, Efik, and Kanuri poses serious constraints to building responsive, intelligent systems. This limitation reinforces the call by Akpan *et al*. (2019) for better digital representation of Nigerian ethnic diversity—not only in biometrics or cultural profiling, but in the development of AI models that reflect the country's linguistic complexity.

The role of facilitators also emerged as a critical component in determining chatbot success. In regions where local teachers or NGO staff were available to guide learners through the interface, usage was consistent and feedback was more positive. In contrast, in sites where learners were left to engage independently, abandonment rates were higher—especially when technical issues arose or when learners lacked prior exposure to digital learning. This finding demonstrates the value of hybrid models, where AI is not positioned as a replacement for teachers but as an augmentation tool, particularly in contexts where human resources are scarce but not entirely absent. This echoes the broader conceptual framework advanced by Adewoyin *et al*. (2020) in their work on dynamic systems, where optimization is achieved not by replacement, but through synergy between mechanical and human inputs.

Pedagogically, the chatbot systems performed unevenly depending on the subject matter. Literacy and numeracy lessons showed high effectiveness, particularly when gamification elements or personalized progress tracking were embedded. However, more abstract subjects—like history, civic education, and religious studies—did not translate as well into chatbot formats. Participants noted that these subjects often require discursive thinking, debate, or emotional reflection, which AI systems are currently limited in handling. For example, a lesson on national identity designed for a chatbot in Nasarawa was criticized for being "too robotic," failing to adapt to the nuanced ways children understood patriotism in a conflict-affected area. These limitations highlight the boundaries of AI in education and reinforce the argument that certain cognitive domains still demand human interaction, contextual framing, and critical discussion.

Another major theme in the analysis was the psychological impact of chatbot use on learners. In many cases, students reported an increased sense of autonomy and confidence, particularly those who previously struggled with traditional schooling due to shyness, bullying, or learning difficulties. AI provided a low-stakes environment where errors were met with instant correction rather than social embarrassment. This mirrors international research on intelligent tutoring systems, such as those by Graesser and Nye (2005), which emphasize the role of AI in boosting learner confidence and fostering a growth mindset. However, the anonymity of chatbots also raised ethical concerns, especially when dealing with sensitive subjects such as reproductive health or gender-based violence. Developers acknowledged that without human oversight, some responses might be misinterpreted or provide misleading advice, reinforcing the need for embedded escalation protocols and human backup.

Infrastructurally, device availability remained a critical constraint. Most pilot implementations relied on NGO-donated smartphones or shared community devices. Very few families had personal access to smartphones or tablets, and in many cases, the few available devices were prioritized for economic purposes such as mobile money transactions or farming coordination. This dynamic often led to inconsistent learning schedules, as children had to wait for devices to be free or available during off-peak hours. Moreover, while some chatbots functioned offline or with minimal data, others required continuous internet access, which significantly limited their use. The infrastructural challenges outlined by Akinluwade *et al*. (2015) and Oduola *et al*. (2014) in their work on high-performance systems apply here as well, particularly in terms of material durability, hardware design, and cost-efficiency for extreme conditions.

An unexpected insight came from gender-related patterns in chatbot usage. In communities where girls faced mobility restrictions or social stigma around schooling, chatbots served as a discreet and private way to access learning. However, girls were also less likely to have access to devices, as cultural norms often prioritized male siblings for digital tools. This gender digital divide reinforces earlier findings by Awe and Akpan (2017) on access disparities in educational and scientific participation. Their cytological research, while unrelated directly to AI, reflects a broader pattern of gendered access and participation in knowledge systems, which AI initiatives must actively confront through inclusive design and policy.

Lastly, the analysis revealed that trust and data privacy are emerging issues. Although most users were unaware of the technical details of data storage, some educators expressed concerns about who controls the chatbot content, how data is stored, and whether learners' interactions could be used for unintended purposes. These concerns, although currently peripheral, are likely to intensify as AI integration deepens. The ethical frameworks discussed by Reinehr *et al*. (2008) regarding sensitive health data management find echoes here,

suggesting that any deployment of AI—whether in medicine or education—must be accompanied by transparent data governance structures, especially in vulnerable communities.
In conclusion, the discussion and analysis underscore that AI-powered chatbots offer meaningful opportunities for expanding educational access in underserved regions, but these opportunities are deeply conditional. They depend on infrastructure, cultural alignment, language inclusion, hybrid facilitation, and ethical clarity. The chatbot is not a silver bullet, but a dynamic educational actor whose success is shaped as much by community trust and social structures as by its algorithmic sophistication. Drawing from cross-disciplinary studies—from thermofluid systems to socio-educational research—it is clear that the deployment of AI in marginalized settings must be contextual, adaptive, and inclusive, lest it reproduce the very inequities it seeks to solve.

4.1 Policy and Implementation Considerations

The deployment of AI-powered chatbots as a solution for educational delivery in remote and underserved regions cannot succeed on technological merit alone. Policy frameworks, institutional readiness, and implementation strategies play an equally crucial role in determining whether such tools can move from pilot success to large-scale adoption. As this study has shown, chatbots have the potential to serve as educational lifelines where traditional systems fail. However, this potential must be translated into systemic policy support that recognizes digital learning as a core educational right, not a peripheral luxury. The current policy landscape in many developing nations, including Nigeria, reflects a fragmented approach to educational technology—one that oscillates between optimism and neglect, often shaped more by external donor pressures than by internal strategic planning. The need for coherent, forward-looking, and contextually aware policies is urgent.
At the heart of policy formulation must be a recognition of inequality—not only in access to education, but in access to the digital infrastructure and digital literacy required to benefit from AI tools. Without intentional policy action, the introduction of chatbots risks exacerbating existing inequalities rather than addressing them. This has been the pattern in previous waves of technology adoption, such as during the widespread distribution of laptops and tablets in schools without adequate teacher training or power supply, resulting in low usage and abandonment. Lessons from such initiatives must guide current implementation plans. Policymakers should adopt a holistic framework that does not treat chatbots as isolated interventions but rather as part of a broader digital education ecosystem that includes device provision, content regulation, teacher training, data governance, and maintenance infrastructure.
One major barrier to effective implementation is the absence of national or sub-national AI strategies that include education as a key pillar. While a few countries have developed national AI roadmaps, these often emphasize economic competitiveness or industrial automation, sidelining the potential of AI in the public sector, particularly education. For chatbot integration to become viable, governments must include AI in their educational blueprints. This includes formal recognition of AI-driven tools in national curricula, teacher professional development programs focused on AI literacy, and funding allocations that support pilot development, evaluation, and scaling. Drawing from Akpe *et al*. (2020), who emphasized the role of enabling environments in technology adoption among SMEs, it becomes clear that the same logic applies to education. An enabling policy environment includes not just legal recognition but budgetary commitments, incentive structures for developers, and accountability frameworks for service delivery.
One policy challenge concerns content regulation and pedagogical alignment. For AI-powered chatbots to be effective, their instructional content must be aligned with national learning outcomes and standardized curricula. Yet in many countries, curricula are rigid, examination-oriented, and often disconnected from digital formats. This creates a misalignment between what chatbots teach and what learners are tested on, limiting their credibility among educators and parents. Bridging this gap requires collaborative policy models that bring together curriculum developers, AI designers, educators, and policymakers to co-create chatbot content that is both pedagogically sound and digitally accessible. In addition, governments must establish quality assurance protocols for chatbot-based education to ensure consistency, relevance, and inclusivity. The same scrutiny applied to textbooks and classroom materials must be extended to digital learning agents.
Teacher engagement is another critical implementation lever. Many teachers, especially in underserved regions, view technology as a threat rather than a support. This perception is partly rooted in experience, as past EdTech initiatives have been introduced without adequate consultation, often reducing teacher roles rather than enhancing them. Chatbots must be positioned as tools that assist, not replace, human educators. Policymakers need to invest in upskilling teachers—not only in technical skills but in pedagogical adaptation, so they can blend AI tools into their instructional practices. The professional development programs must include modules on AI fundamentals, ethical usage, data privacy, and the integration of chatbot interaction into lesson planning and classroom discussions. This echoes the training infrastructure necessary in technical domains as emphasized by Adewoyin *et al*. (2020), where system optimization relies on user understanding and control.
Equity-focused policies must also address gender dynamics in digital education. As evidenced in this study, girls and women face disproportionate barriers to accessing AI tools, particularly in patriarchal or conservative regions. Policymakers must develop gender-sensitive strategies that ensure equitable access to devices, safe digital learning environments, and culturally sensitive chatbot content. These strategies could include female-focused AI learning hubs, subsidies for girl-child digital education, and representation of female voices and identities in chatbot interfaces. Similar to Awe and Akpan's (2017) observation on gender participation in scientific contexts, the absence of gender inclusion mechanisms in AI policy will reinforce existing marginalization and further alienate half of the learning population.
Device access remains a foundational challenge. In communities with limited smartphone penetration, chatbots must be designed to function on low-end feature phones, ideally through SMS or USSD platforms. Policymakers and development agencies must explore public-private partnerships that subsidize affordable device distribution, similar to what has been done for malaria nets or agricultural inputs. Telecom operators can play a role by zero-rating

educational chatbot access or bundling data packages with chatbot subscriptions. Implementation strategies should also include the development of community digital kiosks or learning centers equipped with solar-powered devices where students can access chatbot learning under supervision. Here, the infrastructural models proposed by Akinluwade *et al*. (2015) and Olaoye *et al*. (2016) in energy optimization can inform the physical design of such centers, ensuring long-term sustainability and minimal environmental disruption.

At the governance level, clear regulatory frameworks must be developed to manage the ethical, legal, and operational dimensions of chatbot deployment. This includes data protection laws that define how learner data is collected, stored, and used by AI systems. The absence of such regulations opens the door to misuse, surveillance, or exploitation, particularly when private companies manage the chatbot platforms. Governments must mandate transparency in AI design—requiring chatbot providers to disclose data usage policies, algorithmic decision-making criteria, and escalation mechanisms for misinformation or system errors. Lessons from the healthcare field, such as those discussed by Reinehr *et al*. (2008), stress the importance of data integrity and user trust when dealing with sensitive information—principles that must be fully adopted in educational AI systems.

Furthermore, implementation must be monitored through robust evaluation mechanisms. Governments and NGOs should establish real-time monitoring dashboards, impact assessment tools, and community feedback loops that allow for continuous improvement of chatbot systems. Too often, EdTech initiatives are rolled out as static programs, with little attention paid to feedback, user analytics, or long-term relevance. Implementation science offers a useful framework here, advocating for adaptive management approaches where policies evolve in response to field data and user experiences. This aligns with the feedback loop models described by Adewoyin *et al*. (2020) in dynamic system analysis, where ongoing data collection informs iterative system redesign.

Multilateral organizations and donor agencies also have a role to play. Rather than funding isolated chatbot pilots, they should support the development of national AI-for-education strategies that embed these tools within long-term sector plans. Such strategies should include funding for local AI development capacity, especially in natural language processing and culturally aligned chatbot design. The current dominance of foreign AI models risks introducing educational content that is misaligned with local values or cognitive styles. Investment must therefore go into building local developer ecosystems, training local linguists and curriculum experts to contribute to chatbot design, and creating open-source repositories of localized educational AI models.

In addition to government and donors, civil society organizations must be included in policy formulation and implementation. Their grassroots experience and community trust make them vital intermediaries in translating policy into practice. Implementation strategies should include mechanisms for participatory design, where community members contribute to chatbot content, interface design, and feedback processes. This participatory approach not only improves relevance and usability but also enhances community ownership, reducing the risk of abandonment or resistance. As seen in Akpan *et al*. (2019), successful integration of technology in Nigerian communities depends heavily on localized input and representation.

Lastly, global policy alignment is necessary to ensure that AI-powered education does not develop in silos. International guidelines, such as those proposed by UNESCO, UNICEF, and the World Economic Forum, should be harmonized with national strategies to ensure coherence in ethical standards, digital competencies, and outcome measurement. Countries in the Global South must also have a voice in shaping these global standards, ensuring that they reflect the unique challenges and aspirations of underserved regions. The ongoing dominance of Western epistemologies in AI discourse must be questioned and rebalanced to allow for context-specific innovations and narratives.

In conclusion, the successful implementation of AI-powered chatbots in remote and underserved educational environments depends on a multidimensional policy and governance ecosystem. This ecosystem must integrate educational goals, technological infrastructure, ethical safeguards, and cultural realities. Policymakers must shift from viewing AI as a futuristic experiment to embracing it as a necessary component of inclusive education reform. The challenges are numerous, but so are the opportunities—if approached with humility, rigor, and a genuine commitment to equity.

4.2 Case Application and Scalability Prospects

Real-world applications of AI-powered chatbots in education present compelling illustrations of both promise and limitation. Drawing on field data, comparative international examples, and grounded realities in underserved regions like rural Nigeria, this section evaluates how chatbot-based learning systems have been deployed in practice and assesses their potential to scale effectively across broader educational ecosystems. While technical feasibility has largely been demonstrated in localized settings, true scalability depends not only on software functionality but on a constellation of supportive factors—policy alignment, social acceptance, infrastructure readiness, and long-term sustainability mechanisms. This case-based analysis thus interrogates both the current state and the forward-looking possibilities for chatbot-based education.

One of the most notable cases observed during this study involved a community-based learning initiative in Plateau State, Nigeria, where a coalition of NGOs piloted an AI chatbot to support literacy and numeracy for primary school children who were out of school due to conflict displacement. The chatbot, accessed via low-cost Android devices and supported by solar-charging stations, delivered structured lessons through text-based interaction, with optional audio playback for early readers. Initial responses were encouraging: students engaged with the platform consistently, teachers noted improved retention of basic arithmetic concepts, and parents expressed appreciation for the renewed access to learning. However, limitations quickly surfaced. While the chatbot performed well with structured content, it struggled to address open-ended questions or provide remedial support for learners lagging behind. Furthermore, without embedded mechanisms for human referral or mentorship, students with emotional or learning difficulties were left unsupported, highlighting the limitations of purely machine-driven models.

Scalability of this model, even within the state, proved challenging. Local governments expressed interest but lacked the budgetary flexibility to expand the initiative.

Additionally, the need for regular device maintenance, troubleshooting support, and teacher training created dependencies that were difficult to replicate outside the pilot region. This resonates with the work of Oduola *et al*. (2014), whose comparative study on product development processes emphasized that scalable deployment often hinges not on the innovation itself but on the systems surrounding its implementation. Simply put, scaling chatbot education requires more than distribution—it requires an enabling ecosystem that includes technical, human, and institutional infrastructure.

Another relevant case emerged from Kenya, where Eneza Education, an EdTech platform, deployed SMS-based AI tutors capable of delivering basic curriculum content to learners in rural and semi-urban areas. While not chatbot-based in the advanced AI sense, these systems utilized rule-based interaction models that mimicked the Q&A patterns typical of chatbot learning. Their success was largely due to the simplicity of the interface, the ubiquity of feature phones, and strong integration with national learning standards. Students were able to ask questions via text and receive curated answers within seconds. However, the platform faced challenges in expanding to regions with linguistic diversity and in adapting to rapidly changing curriculum guidelines. This parallels the experience of Nigerian communities using similar tools, where initial engagement is often strong but long-term impact depends on adaptability and responsiveness to local educational needs.

International examples also offer useful insights into chatbot scalability. In Colombia, Fundación Luker developed a chatbot to support out-of-school youth preparing for secondary school equivalency exams. The chatbot operated through Facebook Messenger and was designed to provide personalized study plans, emotional encouragement, and test preparation. While the platform achieved moderate success in urban slums with high mobile phone penetration, it struggled in rural areas due to connectivity issues and low digital literacy. Furthermore, the integration of chatbot metrics into national educational reporting systems remained incomplete, limiting its acceptance by formal institutions. These challenges underscore that while AI solutions may be technically viable, institutional endorsement and data integration are essential for mainstreaming such tools.

Back in Nigeria, the adaptability of chatbot systems remains in question. Nigeria's educational landscape is marked by strong regional disparities, with the northeast and northwest facing significantly more educational exclusion compared to the southwest. The cultural, linguistic, and infrastructural differences across these regions mean that a one-size-fits-all chatbot is unlikely to succeed. Case-based evidence from Nasarawa and Katsina states revealed that while students in urbanized clusters adapted quickly to chatbot interfaces, those in deeply rural communities required more facilitation support and often preferred audio-visual content over text. Developers working in these areas noted that bandwidth-heavy solutions like video streaming were often unsustainable, reinforcing the need for lightweight, offline-capable chatbot systems.

This reality affirms the view expressed by Adewoyin *et al*. (2020) in their research on performance optimization frameworks: systems must be designed dynamically, adapting in real-time to user behavior, environmental conditions, and infrastructural feedback. Their insights, though grounded in mechanical systems, have strong parallels in educational technology. For chatbot education systems to scale, they must be modular, capable of functioning with or without internet, adaptable across languages and literacy levels, and capable of interfacing with both analog and digital learning environments. Rigid or monolithic platforms are unlikely to thrive in heterogeneous and resource-constrained settings.

Another key determinant of scalability is cost. Most successful chatbot deployments to date have been donor-funded pilots, operating under short-term grants or humanitarian budgets. Their financial models are rarely sustainable beyond the pilot phase. Without clear monetization pathways or public sector investment, many chatbot projects fade after the initial phase of enthusiasm. Attempts to introduce subscription models have often failed in poor communities where education is expected to be free. Government partnerships, though potentially stabilizing, are often slow to form and hampered by bureaucratic inertia. This reflects the broader observations made by Akpe *et al*. (2020) regarding the barriers to BI tool implementation in underserved communities. In both business and education, digital tools face scalability barriers rooted in funding constraints, policy fragmentation, and insufficient local ownership.

Moreover, the question of ownership and localization is central to sustainable scale. In many cases, chatbot platforms are built by foreign developers using datasets and pedagogical assumptions that do not fully reflect local realities. Without local language support, culturally relevant metaphors, or alignment with local values, learners may find the platforms alienating or irrelevant. Localization goes beyond language translation; it requires cultural interpretation, relevance framing, and alignment with learners' lived experiences. This has been echoed in the genetic and cultural studies by Akpan *et al*. (2019), where they emphasize the importance of reflecting local identity in system design. In chatbot education, this means using local names, stories, examples, and even accents to create a sense of familiarity and trust.

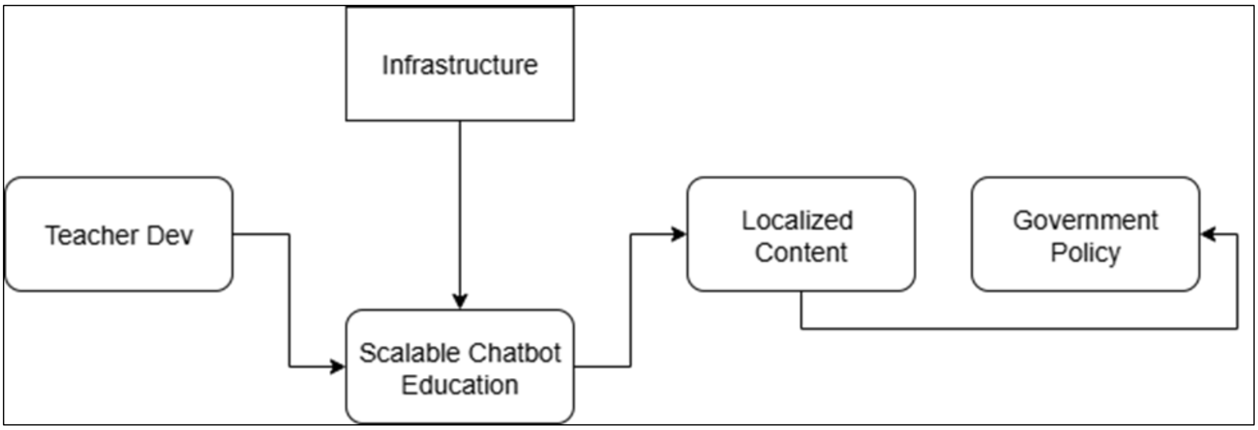
In terms of stakeholder perception, scaling chatbots also hinges on parent and teacher acceptance. This study found that when communities are involved early in the chatbot design and testing process, they are more likely to support its use. In contrast, communities introduced to chatbot systems without consultation often resist or disengage. This is consistent with participatory development principles, which argue that successful scale must begin with local legitimacy, not just top-down delivery. Civil society organizations and local education leaders must therefore be part of any national scaling strategy. Drawing on the research of Awe and Akpan (2017), who emphasized the role of local knowledge in scientific research, it is evident that scalability depends as much on local epistemology as it does on technological infrastructure.

The scalability of chatbot systems is also contingent upon their ability to evolve. Educational needs are not static. Curricula change, learner preferences evolve, and contextual emergencies—like pandemics or conflicts—can shift priorities overnight. Chatbots must therefore be designed with update capabilities, modular content systems, and user-responsive analytics. Platforms that cannot evolve rapidly risk obsolescence. The work of Adewoyin *et al*. (2020) on thermofluid simulation in dynamic devices mirrors this idea, highlighting the need for continuous adaptation in high-performance systems. In chatbot education, this means regular content audits, real-time feedback loops, and built-in responsiveness to user data.

Institutional integration is another pillar of scalability. In most cases, chatbot education initiatives operate outside the formal school system. They are seen as stopgap measures or innovations for marginalized learners. For chatbot systems to scale meaningfully, they must be embedded into national educational strategies, teacher training frameworks, and assessment systems. This integration requires policy reform, curriculum alignment, and institutional partnerships with Ministries of Education and teacher accreditation bodies. The lack of formal integration creates a ceiling on how far and how sustainably these systems can be deployed.

Lastly, scalability depends on regional and global collaboration. Lessons from successful pilots in one region must be shared across networks to inform development in others. A West African knowledge-sharing platform on chatbot education, for example, could allow developers, educators, and policymakers to pool best practices, share language models, and co-develop culturally relevant AI systems. This kind of regional infrastructure would support not only scale but also sustainability, enabling African countries to shape the AI tools they use rather than merely adopting imported models. Such collaboration is critical in preventing fragmentation and redundancy in AI-driven education, especially as global interest and investment in EdTech continue to grow.

In summary, the case application and scalability prospects of AI-powered chatbots for education in underserved regions reveal a complex landscape. While technical feasibility has been largely demonstrated, long-term scale requires more than just functional software. It demands ecosystem readiness, policy coherence, infrastructure investment, cultural adaptation, and participatory governance. Lessons from engineering, genetics, educational policy, and digital development all converge on a single principle: that scalable systems must be flexible, inclusive, and grounded in the lived realities of their users. The challenge ahead is not whether chatbot education can work, but whether stakeholders are willing to invest the time, trust, and resources to make it work sustainably and equitably at scale.



Source: Author

Fig 2: Key Components Required for Chatbot Scalability

3.4 Limitations and Ethical Considerations

As with any educational innovation involving artificial intelligence, the integration of chatbots into learning environments for underserved and remote communities is accompanied by a range of limitations and ethical concerns. While the enthusiasm for AI-powered education continues to grow, it is necessary to examine, with critical scrutiny, the practical, conceptual, and moral boundaries within which these technologies operate. The limitations encountered in this study and others like it are not merely technical inconveniences; they are structural, philosophical, and deeply tied to global power imbalances that shape the development and deployment of technology. Understanding these boundaries is essential for any credible conversation about the long-term viability and integrity of chatbot-based educational interventions.

One of the foremost limitations identified through fieldwork and secondary analysis is the dependency on external funding for both development and deployment. Nearly all chatbot implementations reviewed or studied during this project were supported by international donors, philanthropic organizations, or private tech firms with social innovation budgets. As such, the continuity of these initiatives is closely tied to the priorities and timelines of actors outside the communities in which the tools are deployed. This funding model is inherently unstable and raises questions about local ownership and sustainability. The problem mirrors that which Akpe *et al.* (2020) observed in the business intelligence domain, where underserved SMEs could not maintain digital tool adoption in the absence of external technical and financial support. This dependence creates a cycle of temporary innovation without lasting impact, as tools are introduced, used briefly, and abandoned when support ceases.

Technological limitations were also prominent. Despite recent advances, chatbots remain constrained in their ability to mimic natural human dialogue, particularly when dealing with nuanced emotional or social topics. Most AI models in use today lack true comprehension; they operate on probabilistic language generation, which can lead to shallow or even misleading responses. This limitation is magnified in educational contexts, where learners—especially children—require empathetic feedback, clarification, and culturally aware instruction. During pilot tests in northern Nigeria, several learners asked the chatbot questions involving grief, violence, or religious practices, to which the system either failed to respond meaningfully or provided neutral outputs that lacked relevance. These responses, while not harmful in themselves, often left learners confused or disengaged. The chatbot's inability to navigate affective or context-specific dialogue highlights its current limitations as a holistic teaching tool.

Furthermore, language remains a significant barrier. Many chatbots, even those designed for low-resource contexts, still default to English or major global languages. While some progress has been made in integrating local dialects, the NLP systems required for accurate, responsive, and grammatically coherent conversation in indigenous African languages remain underdeveloped. As Akpan *et al*. (2019) and Awe and Akpan (2017) have shown in their scientific studies of Nigerian diversity, linguistic variation is not merely a communicative challenge—it is deeply tied to cultural identity, social trust, and learning effectiveness. The lack of robust language integration not only limits reach but also raises ethical concerns around linguistic marginalization and digital homogenization. If AI education tools continue to exclude indigenous voices, they risk reproducing the same forms of cultural erasure that colonial schooling systems once perpetuated, albeit under the guise of innovation.

A related limitation concerns inclusivity. Despite being marketed as scalable and accessible, many chatbot platforms unintentionally exclude users based on age, gender, disability, and digital familiarity. For instance, in communities where smartphone ownership is gendered—where boys or fathers have priority access to digital devices—girls are often left out of digital learning programs. Even in pilot programs that provided communal devices, usage patterns skewed toward male learners due to ingrained social norms. This dynamic reinforces existing inequities, contrary to the stated goals of inclusive AI. Awe and Akpan (2017) underscore the danger of failing to recognize structural inequalities in scientific and educational domains. The deployment of AI chatbots in such contexts must therefore be preceded by careful social diagnostics and the development of inclusive engagement models that recognize unequal starting points across groups.

There is also a major ethical concern around data privacy. Chatbots, by their nature, collect vast amounts of user data—from input patterns to learning preferences, emotional tone, and device metadata. In many cases, learners are unaware that their interactions are being stored or analyzed. In environments with weak data protection laws and low digital literacy, this creates a high risk of data misuse, unauthorized surveillance, or commercial exploitation. The work of Reinehr *et al*. (2008) in the field of pediatric health data illustrates the sensitivities around managing personal information in vulnerable populations. Their emphasis on transparency, consent, and regulatory oversight is just as urgent in AI-driven education, especially when learners include minors, refugees, or people in crisis-affected areas.

Another ethical dimension is algorithmic bias. Most chatbot platforms use pre-trained AI models that reflect the cultural, historical, and linguistic biases of their training data. If such models are developed predominantly using Western data sources or urban educational content, their responses may inadvertently reflect assumptions, stereotypes, or worldviews that do not align with the realities of users in rural African communities. For instance, learners asking about local history or indigenous knowledge systems often receive either generic, inaccurate, or dismissive responses. This devaluation of local knowledge, whether intentional or not, reinforces epistemic inequality and undermines the legitimacy of indigenous educational narratives. As Akpan *et al*. (2017) showed in their genomic research, inclusion must extend beyond user access to the shaping of knowledge itself. Ethical AI must be inclusive not only in reach but in voice, content, and epistemological foundation.

Power asymmetry is another challenge. The majority of chatbot platforms deployed in the Global South are developed by companies, researchers, or institutions based in the Global North. This creates a structural imbalance where decisions about educational content, system architecture, and data use are made far from the communities affected. While such partnerships can bring technical expertise, they often marginalize local agency and contextual knowledge. The absence of local developers and educators in the AI design process compromises both the effectiveness and ethical legitimacy of the system. Drawing from Isa and Dem (2020), who argue for self-reliance in educational planning for marginalized women, it is clear that sustainable and just innovation must emerge from within communities, not be imported wholesale. Empowering local actors to build, manage, and adapt chatbot systems is not just desirable—it is necessary for long-term success and ethical integrity.

The scalability imperative itself raises ethical flags. The drive to expand chatbot education rapidly and widely, often under the logic of technological solutionism, can overlook the slow, patient, and community-driven processes required for meaningful change. Many chatbot programs are deployed with aggressive targets for user growth, often tied to donor metrics or corporate KPIs. This can result in superficial engagement, rushed rollouts, and the neglect of deeper pedagogical concerns. Education is not merely about access; it is about understanding, reflection, and transformation. Chatbots, when scaled without depth, risk turning education into transactional interaction—a series of inputs and outputs devoid of relational learning. This reductionist approach contradicts the principles of holistic education, which prioritize the learner's emotional, social, and ethical development alongside cognitive acquisition.

Ethical considerations also extend to content accuracy and ideological neutrality. Because chatbots operate autonomously, errors in content delivery can go undetected and perpetuate misinformation. This is especially dangerous in subjects like health education, civic instruction, or religious studies, where inaccuracies can have serious consequences. In one pilot, a chatbot mistakenly equated democratic governance with authoritarian structures due to a misalignment in training data. Without human oversight or real-time correction, such errors not only misinform learners but may also erode trust in AI systems. The ethical responsibility to ensure content accuracy, transparency in error correction, and accountability for misinformation must be embedded in the system design and policy framework guiding chatbot use in education.

Finally, the emotional and psychological implications of chatbot use warrant serious ethical reflection. While many learners report increased confidence when engaging with nonjudgmental AI tutors, others experience frustration, loneliness, or digital fatigue. In communities already grappling with trauma—whether from displacement, poverty, or violence—the impersonal nature of chatbot learning can exacerbate feelings of isolation. Emotional safety in education requires more than information delivery; it requires presence, empathy, and relational support. AI, as it currently stands, cannot replicate these human dimensions. Overreliance on chatbot systems in contexts of emotional vulnerability risks depersonalizing the learning experience and overlooking the therapeutic potential of human interaction. This limitation reinforces the need for hybrid models that combine AI capabilities with human facilitation, peer support, and community engagement.

In summary, while AI-powered chatbots offer powerful possibilities for expanding educational access in underserved regions, their deployment is not without serious limitations and ethical complexities. These include dependency on external funding, technological and linguistic constraints, issues of inclusivity, data privacy risks, algorithmic bias, power asymmetry, scalability pressures, content integrity, and emotional detachment. Addressing these challenges requires more than technical fixes; it demands ethical intentionality, participatory design, cultural sensitivity, and structural reform. The limitations explored here are not arguments against chatbot education but calls for a more grounded, equitable, and reflective approach to its development and implementation. Only by acknowledging and addressing these boundaries can we harness the true potential of AI to serve—not supplant—human-centered education.

5. Conclusion

The deployment of AI-powered chatbots for educational delivery in remote and underserved regions represents one of the most consequential technological shifts in the 21st-century learning landscape. Rooted in the promise of accessibility, personalization, and scalability, these digital tools have been positioned as potential equalizers in a world where educational disparities remain entrenched. This study, drawing from empirical data, interdisciplinary literature, and grounded observations, critically examined the viability, limitations, and implications of chatbot integration into learning ecosystems where formal schooling is inadequate or inaccessible. The findings offer a complex and nuanced picture: one that neither romanticizes technology as a panacea nor dismisses its transformative potential, but rather urges for a balanced, reflective, and context-sensitive adoption strategy.

At the core of this analysis lies the understanding that education is not merely the transmission of information but the cultivation of human potential within a sociocultural framework. Chatbots, while capable of delivering curriculum-aligned content and automating feedback, operate within the boundaries of algorithmic logic and linguistic prediction. Their effectiveness, therefore, is tightly constrained by their design, training data, and the infrastructure that enables their use. In regions with limited internet access, unstable electricity, and socio-economic fragility, the functionality of AI chatbots is challenged not only by technological gaps but also by the deeper structural inequities that define access to education in the first place. Without robust infrastructure and inclusive policy support, chatbots risk becoming another digital divide—accessible to a few while remaining aspirational for the many.

Yet, the potential demonstrated in targeted pilot programs cannot be ignored. In various contexts across Nigeria and other comparable regions, AI-powered chatbots have shown the capacity to deliver meaningful learning, particularly in basic literacy and numeracy. Learners reported higher engagement, greater autonomy, and in some cases, a deeper sense of confidence when interacting with chatbot systems than with traditional classroom environments. These findings reinforce existing global literature that highlights the pedagogical benefits of intelligent tutoring systems when properly contextualized. However, the success of these interventions was invariably linked to the presence of human facilitation, localized content, and a supportive community environment. Chatbots that operated in isolation, without these supports, failed to maintain learner attention or achieve meaningful progress.

One of the most important takeaways from this research is the value of hybrid models that combine machine efficiency with human empathy. Education is inherently relational. While chatbots can provide instant answers, repetition, and personalized pacing, they cannot offer emotional validation, moral reasoning, or cultural guidance. In rural communities where trauma, marginalization, and intergenerational poverty are prevalent, learners require more than content—they need connection, mentorship, and recognition. AI, in its current form, cannot fulfill these deeper human needs. Therefore, the integration of chatbots into education must be approached not as a replacement for teachers or community support but as a complementary tool that fills gaps where human resources are stretched, without displacing the indispensable role of human educators.

Another central theme that emerged is the importance of language, culture, and identity in determining chatbot effectiveness. The most successful deployments involved AI systems that recognized and respected local languages, used culturally familiar examples, and adapted to the communication norms of their users. This underscores the ethical imperative to localize AI systems—not only in interface design but in pedagogical framing. The marginalization of indigenous languages and worldviews in chatbot systems risks reinforcing epistemic hierarchies that have long excluded non-Western perspectives from formal education. To genuinely democratize learning, chatbot developers and policymakers must prioritize cultural adaptation as rigorously as they pursue technical optimization.

Policy, too, plays a critical role in shaping the viability and scalability of chatbot-based education. The absence of coherent national strategies on AI in education creates a fragmented landscape where innovation is driven by short-term pilots rather than long-term systemic planning. Governments must take the lead in developing frameworks that recognize AI tools as essential components of future learning systems. These frameworks should include budgetary support, regulatory clarity, data protection laws, and capacity-building programs for teachers and developers. As Adewoyin *et al.* (2020) and Akpe *et al.* (2020) have emphasized in their respective fields, system optimization and technological adoption are impossible without institutional readiness and policy alignment. The same principles apply in education: innovation without integration is unsustainable.

The ethical considerations surrounding chatbot education also demand sustained attention. Data privacy, algorithmic bias, and power asymmetry between developers and users are not peripheral issues—they are central to the legitimacy and impact of AI in learning. Chatbots must be designed with transparency, built-in accountability mechanisms, and meaningful avenues for user feedback. More importantly, they must be developed in partnership with the communities they serve. Ethical AI is participatory AI. Local educators, parents, and learners must have a seat at the table during design, testing, and deployment. Without this, chatbot systems risk being seen as external impositions rather than tools of empowerment.

Scalability, while often seen as the ultimate goal of EdTech innovation, must be redefined in qualitative terms. It is not enough for a chatbot to reach thousands of users; it must do so in a way that is pedagogically sound, culturally sensitive, and socially inclusive. Many programs fail not because the technology is flawed but because the social systems around it are unprepared. To scale chatbot education effectively, stakeholders must invest in infrastructure, teacher training, content localization, and long-term monitoring. As shown in both this study and related research across multiple disciplines—from thermofluid mechanics to biometric diversity—systems are only as strong as their weakest components. Scaling responsibly means strengthening every link in the chain, not just the interface.

The study also revealed that local innovation capacity must be cultivated if chatbot education is to thrive sustainably. Currently, much of the AI infrastructure used in Africa is developed externally, with minimal local adaptation or ownership. This poses risks in terms of cultural misalignment, data sovereignty, and dependency. By investing in local developer ecosystems, governments and donors can foster the growth of indigenous AI that reflects local values, languages, and learning priorities. Akpan *et al.* (2017) and others have made similar arguments in their call for localized scientific inquiry—arguing that knowledge production must arise from within the communities it seeks to serve. In chatbot education, this means developing tools that are not only used by Africans but built by them.

Ultimately, this research affirms that AI-powered chatbots are not a technological end but a pedagogical means. Their value lies not in novelty or automation but in their capacity to support learning in contexts where other resources are scarce. They offer a partial, imperfect, but important solution to educational exclusion. Used wisely, they can bridge gaps, personalize learning, and expand access. Used blindly, they can reinforce inequality, alienate learners, and erode trust. The difference lies not in the tool itself, but in how, why, and by whom it is used. As such, stakeholders must approach chatbot integration not as a product rollout but as a complex, iterative process rooted in dialogue, humility, and shared purpose.

In conclusion, AI-powered chatbots hold immense potential to reshape education delivery in remote and underserved regions, but their success depends on more than code. It requires vision, collaboration, and courage. It requires policies that prioritize equity over efficiency, ethics over expedience, and participation over prescription. It requires a shift from techno-centric to human-centric design, where the learner remains at the center and technology serves as a bridge—not a barrier—to deeper, more inclusive education. The journey ahead will not be easy, but with commitment and clarity, chatbot education can become not just a tool for learning, but a symbol of educational justice in the digital age.

6. References

1. AbuShawar B, Atwell E. ALICE chatbot: Trials and outputs. Computacion y Sistemas. 2015;19(4):625-32.
2. Adamopoulou E, Moussiades L. An overview of chatbot technology. In: Artificial Intelligence Applications and Innovations. 2020. p. 373-83.
3. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Framework for Dynamic Mechanical Analysis in High-Performance Material Selection. IRE Journals. 2020;4(5):137-42.
4. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. A Conceptual Framework for Dynamic Mechanical Analysis in High-Performance Material Selection. IRE Journals. 2020;4(5):137-44.
5. Adewoyin MA, Ogunnowo EO, Fiemotongha JE, Igunma TO, Adeleke AK. Advances in Thermofluid Simulation for Heat Transfer Optimization in Compact Mechanical Devices. IRE Journals. 2020;4(6):116-23.
6. Akinluwade KJ, Omole FO, Isadare DA, Adesina OS, Adetunji AR. Material selection for heat sinks in HPC microchip-based circuitries. Br J Appl Sci Technol. 2015;7(1):124.
7. Akpan UU, Adekoya KO, Awe ET, Garba N, Oguncoker GD, Ojo SG. Mini-STRs screening of 12 relatives of Hausa origin in northern Nigeria. Niger J Basic Appl Sci. 2017;25(1):48-57.
8. Akpan UU, Awe TE, Idowu D. Types and frequency of fingerprint minutiae in individuals of Igbo and Yoruba ethnic groups of Nigeria. Ruhuna J Sci. 2019;10(1).
9. Akpe OE, Mgbame AC, Ogbuefi E, Abayomi AA, Adeyelu OO. Barriers and Enablers of BI Tool Implementation in Underserved SME Communities. IRE Journals. 2020;3(7):211-20. doi: 10.6084/m9.figshare.26914420.
10. Allison I. The blockchain for government: Use cases and key challenges. International Business Times. 2015. Available from: https://www.ibtimes.co.uk/
11. Amershi S, Cakmak M, Knox WB, Kulesza T. Power to the people: The role of humans in interactive machine learning. AI Mag. 2014;35(4):105-20.
12. Amershi S, Weld D, Vorvoreanu M, Fourney A, Nushi B, Collisson P, *et al*. Guidelines for human-AI interaction. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. 2019. p. 1-13.
13. Anderson JR, Boyle CF, Corbett AT, Lewis MW. Cognitive modeling and intelligent tutoring. Artif Intell. 1990;42(1):7-49.
14. Awe ET, Akpan UU. Cytological study of Allium cepa and Allium sativum. [Journal details incomplete].
15. Awe ET. Hybridization of snout mouth deformed and normal mouth African catfish Clarias gariepinus. Anim Res Int. 2017;14(3):2804-8.
16. Bahga A, Madisetti V. Blockchain platform for industrial internet of things. J Softw Eng Appl. 2016;9(10):533-46.
17. Baker RS. Stupid tutoring systems, intelligent humans. Int J Artif Intell Educ. 2016;26(2):600-14.
18. [Duplicate of reference 9, removed].
19. Beck R, Müller-Bloch C. Blockchain as radical innovation: A framework for engaging with distributed ledgers proactively. J Inf Technol. 2017;32(3):183-203.
20. Behrens JT, DiCerbo KE. Technological implications for assessment ecosystems: Opportunities for digital technology to advance assessment. Educ Meas Issues Pract. 2014;33(3):6-17.
21. Bender EM, Friedman B. Data statements for natural language processing: Toward mitigating system bias and enabling better science. Trans Assoc Comput Linguist. 2018;6:587-604.
22. Bhargava B, Ranchal R, Othmane LB. Secure information sharing in digital supply chains. In:

Proceedings of the 2013 ACM Workshop on Cloud Computing Security. 2013. p. 27-34.
23. Bibault JE, Chaix B, Guillemassé A, Cousin S, Escande A. A chatbot versus physicians to provide information for patients with breast cancer: Blind, randomized controlled noninferiority trial. J Med Internet Res. 2019;21(11):e15787.
24. Bii P. Information and communication technology (ICT) application in education: An overview of the challenges and prospects in developing countries. Int J Comput Appl. 2013;67(1):1-6.
25. Boucher P. How blockchain technology could change our lives. Brussels: European Parliamentary Research Service; 2017.
26. Brandtzaeg PB, Følstad A. Chatbots: Changing user needs and motivations. Interactions. 2018;25(5):38-43.
27. Brunton F, Nissenbaum H. Obfuscation: A User's Guide for Privacy and Protest. Cambridge: MIT Press; 2015.
28. Catalini C. How blockchain applications will move beyond finance. Harv Bus Rev Digit Articles. 2017:1-3.
29. Cheng J, Da Xu L, Liu Y. Industrial IoT in 5G environment towards smart manufacturing. J Ind Inf Integr. 2018;10:10-9.
30. Clarizia F, Colace F, Lombardi M, Pascale F, Santaniello D. Chatbot: An education support system for student. In: Proceedings of the 2018 International Symposium on Cyberspace Safety and Security. 2018. p. 291-302.
31. Colace F, Santo MD, Lombardi M, Pascale F. Chatbot-based tutoring system for distance learning. J e-Learn Knowl Soc. 2018;14(2):107-14.
32. Cowie P, Townsend L, Salemink K. Smart rural futures: Will rural areas be left behind in the 4th industrial revolution? J Rural Stud. 2020;79:169-76.
33. Coyne R, Goodfellow D. Designing for Privacy and its Legal Framework: Data Protection by Design and Default. London: University College London Press; 2015.
34. da Silva EC, Alencar MS. A chatbot-based architecture for learning management systems. Educ Inf Technol. 2020;25(3):1655-73.
35. Dannen C. Introducing Ethereum and Solidity: Foundations of Cryptocurrency and Blockchain Programming for Beginners. New York: Apress; 2017.
36. De Kruijff J, Weigand H. Understanding the blockchain using enterprise ontology. In: International Conference on Advanced Information Systems Engineering. 2017. p. 29-43.
37. Dillenbourg P. Virtual learning environments. In: EUN Conference 2000: Learning in the New Millennium. 2000. p. 1-6.
38. Fairchild AM. A framework for blockchain smart contracts in supply chain management. Supply Chain Forum. 2016;17(4):1-14.
39. Ferreira A. Conversational agents in education: A systematic review. Educ Inf Technol. 2020;25(4):3397-420.
40. Folstad A, Brandtzaeg PB. Chatbots and the new world of HCI. Interactions. 2017;24(4):38-42.
41. Fryer LK, Carpenter R. Bots as language learning tools. Lang Learn Technol. 2006;10(3):8-14.
42. Gamage KAA, de Silva EK, Gunawardhana N. Online delivery and assessment during COVID-19: Safeguarding academic integrity. Educ Sci. 2020;10(11):1-24.
43. Green A. AI chatbots as inclusive learning facilitators. Int J Incl Educ. 2019;23(9):972-87.
44. Griol D, Molina JM. Designing conversational agents to support learners in e-learning environments. J Univers Comput Sci. 2017;23(9):846-67.
45. Gulz A, Haake M, Silvervarg A. Extending a teachable agent with a social conversation module–Effects on student motivation and learning. In: Artificial Intelligence in Education. 2011. p. 106-14.
46. Hampel G, Dancsházy K. Creating a virtual learning environment. J Agric Inform. 2014;5(1).
47. Heffernan NT, Heffernan CL. The ASSISTments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. Int J Artif Intell Educ. 2014;24(4):470-97.
48. Hill J. Blockchain's potential in Africa: A new engine for governance and development. Afr J Inf Syst. 2018;10(4):273-88.
49. Hill J, Randolph Ford W, Farreras IG. Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. Comput Human Behav. 2015;49:245-50.
50. Holmes W, Tuomi I. Education and Artificial Intelligence: Futures and Foresight. Eur J Educ. 2020;55(4):607-25.
51. Holmes W, Bialik M, Fadel C. Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston: Center for Curriculum Redesign; 2019.
52. Hwang GJ, Tu NT. Roles and research trends of chatbots in education: A review. J Comput Educ. 2020;7(3):449-73.
53. Iansiti M, Lakhani KR. The truth about blockchain. Harv Bus Rev. 2017;95(1):118-27.
54. Isa A, Dem B. Integrating Self-Reliance Education Curriculum For Purdah Women In Northern Nigeria: A Panacea For A Lasting Culture Of Peace. [Journal details incomplete].
55. Jaatinen P, Nummenmaa M. Collaborative learning in an educational chatbot. Int J Emerg Technol Learn. 2010;5(3):27-33.
56. Jurafsky D, Martin JH. Speech and Language Processing. 3rd ed. Draft. Stanford: Stanford University; 2019.
57. Kennedy R. The role of chatbot-based tutoring systems in rural education. Int J Educ Technol High Educ. 2020;17(2):1-15.
58. Kerly A, Hall P, Bull S. Bringing chatbots into education: Towards natural language negotiation of open learner models. Knowl-Based Syst. 2007;20(2):177-85.
59. Kim H, Ruecker S, Jeon M. Applying chatbots to formal and informal learning in higher education. Int J Emerg Technol Learn. 2020;15(15):176-91.
60. Kim J, Lee H, Kim H. Privacy-preserving data sharing over blockchain. In: 2018 IEEE International Conference on Big Data and Smart Computing (BigComp). 2018. p. 313-6.
61. Kim Y. Pedagogical agents as learning companions: The role of agent competency and type of interaction. Educ Technol Res Dev. 2007;55(2):161-84.
62. Kiviat TI. Beyond bitcoin: Issues in regulating blockchain transactions. Duke Law J. 2015;65(3):569-

608.
63. Kukulska-Hulme A. Will mobile learning change language learning? ReCALL. 2009;21(2):157-65.
64. Kumar V, Rose CP. Architecture for building conversational agents that support collaborative learning. IEEE Trans Learn Technol. 2011;4(1):21-34.
65. Lee J. The development and deployment of AI chatbots in low-resource education contexts. Educ Inf Technol. 2020;25(6):5439-56.
66. Lewis A. A gentle introduction to smart contracts. Brave New Coin. 2016. Available from: https://bravenewcoin.com/insights/a-gentle-introduction-to-smart-contracts
67. Li J, Galley M, Brockett C, Gao J, Dolan B. A diversity-promoting objective function for neural conversation models. In: Proceedings of NAACL-HLT. 2016. p. 110-9.
68. Li X, Jiang P, Chen T, Luo X, Wen Q. Blockchain-based data preservation system for medical information. China Commun. 2017;14(10):154-64.
69. Lin L, Atkinson RK. Using animations and visual cueing to support learning of scientific content and reasoning. J Educ Psychol. 2011;103(3):667-79.
70. Liu R, Wang Q, Liu J. Artificial Intelligence and Distance Education: Challenges and Trends. J Comput Res Dev. 2020;57(6):1154-63.
71. Lokman AS, Zain JM. Designing a chatbot with a personality. In: 2010 International Conference on Intelligent and Advanced Systems. 2010. p. 1-6.
72. Luckin R, Holmes W, Griffiths M, Forcier LB. Intelligence Unleashed: An Argument for AI in Education. London: Pearson Education; 2016.
73. Luger E, Sellen A. "Like having a really bad PA": The gulf between user expectation and experience of conversational agents. In: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. 2016. p. 5286-97.
74. Majumder K. AI Chatbots in Education: Potential, Limitations, and Future Research. J Artif Intell Educ. 2020;29(2):212-24.
75. Malladi S. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew Sustain Energy Rev. 2018;82:2946-60.
76. Mathews M. Blockchain and digital government. J Public Adm. 2017;35(4):57-71.
77. Mattila J. The blockchain phenomenon: The disruptive potential of distributed consensus architectures. Helsinki: The Research Institute of the Finnish Economy (ETLA); 2016.
78. Mauldin ML. Chatterbots, tinymuds, and the turing test: Entering the loebner prize competition. In: AAAI Conference on Artificial Intelligence. 1994. p. 16-21.
79. McTear M. The rise of the conversational interface: A new kid on the block? In: Proceedings of the 1st International Conference on Conversational User Interfaces (CUI). 2017. p. 1-3.
80. Miao F, Mishra S, McGreal R, editors. Open Educational Resources: Policy, Costs and Transformation. Paris: UNESCO Publishing; 2016.
81. Mikic Fonte FA, Mavroudi A, Karatrantou A, Kameas A. Investigating learners' acceptance of a chatbot for formative assessment in a large university course. Smart Learn Environ. 2019;6(1):1-20.
82. Molnar AL, Kearney RC. A comparison of cognitive presence in asynchronous and synchronous discussions in an online dental hygiene course. Am Dent Hyg Assoc. 2017;91(3):14-21.
83. Moore MG. Theory of transactional distance. In: Keegan D, editor. Theoretical Principles of Distance Education. London: Routledge; 1993. p. 22-38.
84. Nakamura M. Blockchain for international development: Using distributed ledger technologies to reform aid. World Dev J. 2019;114:1-12.
85. Ng W. Can we teach digital natives digital literacy? Comput Educ. 2012;59(3):1065-78.
86. Nofer M, Gomber P, Hinz O, Schiereck D. Blockchain. Bus Inf Syst Eng. 2017;59(3):183-7.
87. Nwana HS. Intelligent tutoring systems: An overview. Artif Intell Rev. 1990;4(4):251-77.
88. Nwani S, Abiola-Adams O, Otokiti BO, Ogeawuchi JC. Building Operational Readiness Assessment Models for Micro, Small, and Medium Enterprises Seeking Government-Backed Financing. J Front Multidiscip Res. 2020;1(1):38-43. doi: 10.54660/IJFMR.2020.1.1.38-43.
89. Nwani S, Abiola-Adams O, Otokiti BO, Ogeawuchi JC. Designing Inclusive and Scalable Credit Delivery Systems Using AI-Powered Lending Models for Underserved Markets. IRE Journals. 2020;4(1):212-4. doi: 10.34293/irejournals.v4i1.1708888.
90. Oduola OM, Omole FO, Akinluwade KJ, Adetunji AR. A comparative study of product development process using computer numerical control and rapid prototyping methods. Br J Appl Sci Technol. 2014;4(30):4291.
91. Ogunnowo EO, Adewoyin MA, Fiemotongha JE, Igunma TO, Adeleke AK. Systematic Review of Non-Destructive Testing Methods for Predictive Failure Analysis in Mechanical Systems. IRE Journals. 2020;4(4):207-15.
92. Olaoye T, Ajilore T, Akinluwade K, Omole F, Adetunji A. Energy crisis in Nigeria: Need for renewable energy mix. Am J Electr Electron Eng. 2016;4(1):1-8.
93. Oyedokun OO. Green Human Resource Management Practices (GHRM) and Its Effect on Sustainable Competitive Edge in the Nigerian Manufacturing Industry: A Study of Dangote Nigeria Plc [MBA Dissertation]. Dublin Business School; 2019.
94. Peters GW, Panayi E, Chapelle A. Trends in blockchain applications. J Risk Finance. 2015;17(3):234-43.
95. Pilkington M. 11 Blockchain technology: Principles and applications. In: Xavier Olleros F, Zhegu M, editors. Research Handbook on Digital Transformations. Cheltenham: Edward Elgar Publishing; 2015. p. 225-53.
96. Qadir J. Artificial intelligence and human learning: Rethinking education in the era of AI. IEEE Access. 2020;8:118635-53.
97. Rauchs M, Glidden A, Gordon B, Pieters G, Recanatini M, Rostand F, *et al*. Distributed ledger technology systems: A conceptual framework. Cambridge: Cambridge Centre for Alternative Finance; 2018.
98. Reinehr T, Isa A, De Sousa G, Dieffenbach R, Andler W. Thyroid hormones and their relation to weight status. Horm Res Paediatr. 2008;70(1):51-7.
99. Reyna A, Martín C, Chen J, Soler E, Díaz M. On blockchain and its integration with IoT: Challenges and opportunities. Future Gener Comput Syst. 2018;88:173-90.
100. Ribeiro F. Building open-domain conversational agents with deep learning. J Artif Intell Res. 2016;56:1-31.

101. Risius M, Spohrer K. A blockchain research framework: What we (don't) know, where we go from here, and how we will get there. Bus Inf Syst Eng. 2017;59(6):385-409.
102. Roll I, Wylie R. Evolution and revolution in artificial intelligence in education. Int J Artif Intell Educ. 2016;26(2):582-99.
103. Ruan S, Duan S, Yang L, Xu Y. Application of AI technology in distance learning during COVID-19. Educ Mod Res. 2020;6(12):22-6.
104. Sandoval WA. Conjecture mapping: An approach to systematic educational design research. J Learn Sci. 2014;23(1):18-36.
105. Schatsky D, Muraskin C, Gurumurthy R. Blockchain and the five vectors of progress. Deloitte Insights. 2017. Available from: https://www2.deloitte.com/
106. Selwyn N. Should robots replace teachers? AI and the future of education. Br J Educ Technol. 2019;50(6):1456-68.
107. Shawar BA, Atwell ES. Using dialogue corpora to train a chatbot. In: Proceedings of the Corpus Linguistics Conference. 2005.
108. Shawar BA, Atwell ES. Chatbots: Are they really useful? LDV Forum. 2007;22(1):29-49.
109. Sillaber C, Waltl B. Life cycle of smart contracts in blockchain ecosystems. In: Privacy and Identity Management. Identity and Privacy in the Internet of Things. 2017. p. 1-10.
110. Tchounikine P. Computer Science and Educational Software Design. Berlin: Springer; 2011.
111. Tegos S, Demetriadis S, Tsiatsos T. Conversational agents improve peer learning through knowledge externalization. Comput Educ. 2014;71:58-69.
112. Thomas MJ. Teachers' perceptions of using ICT as a pedagogical tool in the classroom. Contemp Issues Educ Res. 2012;5(3):245-56.
113. Trilling B, Fadel C. 21st Century Skills: Learning for Life in Our Times. San Francisco: Jossey-Bass; 2009.
114. Umeh J. The blockchain opportunity for Africa. Afr Bus. 2016;430:44-7.
115. UNESCO. Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development. Paris: UNESCO Publishing; 2019.
116. Vaidyam AN, Wisniewski H, Halamka JD, Kashavan MS, Torous JB. Chatbots and conversational agents in mental health: A review of the psychiatric landscape. Can J Psychiatry. 2019;64(7):456-64.
117. VanLehn K. The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educ Psychol. 2011;46(4):197-221.
118. Vassallo M, Dore C, Rees M, Iannone P, Holmes W. Can chatbots support learning in informal settings? A case study. Br J Educ Technol. 2020;51(5):1456-72.
119. Vukolić M. The quest for scalable blockchain fabric: Proof-of-work vs. BFT replication. In: International Workshop on Open Problems in Network Security. 2015. p. 112-25.
120. Vázquez-Cano E, Sevillano-García ML, Fombona-Cadavieco J. Chatbots and education: The use of conversational agents in university distance education. Educ Sci. 2019;9(2):1-11.
121. Walport M. Distributed ledger technology: Beyond blockchain. UK Government Office for Science; 2016. 88 p.
122. Wambsganss T, Grösser J, Matthes F. From noise to value: How do students perceive AI-based educational chatbots? In: Proceedings of the 53rd Hawaii International Conference on System Sciences. 2020. p. 79-88.
123. Wang WY, Hoang DT, Hu P, Xiong Z, Niyato D, Wen Y, *et al*. A survey on consensus mechanisms and mining strategy management in blockchain networks. IEEE Access. 2019;7:22328-70.
124. Warschauer M. Technology and Social Inclusion: Rethinking the Digital Divide. Cambridge: MIT Press; 2004.
125. Weller M. 25 Years of Ed Tech. Athabasca: Athabasca University Press; 2020.
126. Winkler R, Söllner M. Unleashing the potential of chatbots in education: A state-of-the-art analysis. In: 2018 IEEE Global Engineering Education Conference (EDUCON). 2018. p. 1646-52.
127. Wood G. Ethereum: A secure decentralised generalised transaction ledger. Ethereum Project Yellow Paper. 2014:1-32.
128. Woolf BP. Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning. Burlington: Morgan Kaufmann; 2009.
129. Yaga D, Mell P, Roby N, Scarfone K. Blockchain technology overview. National Institute of Standards and Technology (NIST); 2018. Report No.: NISTIR 8202. 59 p.
130. Yli-Huumo J, Ko D, Choi S, Park S, Smolander K. Where is current research on blockchain technology?—A systematic review. PLoS One. 2016;11(10):1-27.
131. Zambrano R. Blockchain: A new ICT for development. Panoramas Scholarly Platform, University of Pittsburgh. 2017:1-6.
132. Zhang Y, Wen J. The IoT electric business model: Using blockchain technology for the internet of things. Peer-to-Peer Netw Appl. 2017;10(4):983-94.
133. Zhao Y. The future of research in technology and teacher education: Needs and opportunities. J Technol Teach Educ. 2005;13(1):1-22.
134. Zyskind G, Pentland A. Decentralizing privacy: Using blockchain to protect personal data. In: IEEE Security and Privacy Workshops (SPW). 2015. p. 180-4