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DEVELOPING AN AI-BASED PERSONALIZED LEARNING SYSTEM FOR STUDENTS WITH INTERRUPTED EDUCATION IN SUDAN

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Abstract. This study examines the revolutionary capacity of Artificial Intelligence (AI) in tackling the significant challenge of Sudan. Sudan has been greatly affected by war and displacement, leading to widespread school closures and interruptions in education. There are millions of children and teens whose education has been disrupted, creating big holes in their learning and a massive need for adaptive, accessible, and individualized educational solutions. This study presents an AI-driven framework, developed to build personalized learning paths that are based on each student's needs, their prior knowledge and learning pace. The method uses AI parts like learner profiling, adaptive content delivery, and intelligent tutoring solutions that work with new technologies that are specific to the situation, such mobile-first interfaces and local dialects assistance, offline-first capability, and community-validated content. A possible deployment scenario in a Sudanese refugee camp exemplifies the practical implementation and prospective results. The work examines anticipated benefits—including enhanced engagement and improved learning outcomes—while critically analyzing limitations, risks, and ethical considerations such as data privacy, algorithmic bias, and equitable access. This paper aims to give a strong conceptual base for creating AI-powered educational tools that can be used by many people and have a big effect on educational initiatives, providing a means to reinstate

educational continuity and empower a generation of learners in crisis-affected regions.

Keywords: Personalized learning, Knowledge tracing, Low-bandwidth edtech, Learning analytics, Sudan, Education in emergencies

1. Introduction

According to Education Cannot Wait (2024) that roughly 222 million children and adolescents in crisis-affected areas needed an immediate response in education. As of June 2025, ongoing conflicts persist in Yemen, Sudan, and Ukraine, with education becoming increasingly entangled in the crossfire of international strife. Beyond disrupting physical infrastructure, these conflicts jeopardize children's cognitive, emotional, and developmental growth. Emergency education has been recognized as a strategic pillar of human security programs [1]. UNICEF (2024) [2] reports that children in conflict areas have less than half the likelihood of attending school, with many experiencing acute trauma, educational disruptions, and hazardous living conditions. Due to prolonged hostilities, forced displacement, and humanitarian crises, millions of children and youth in Sudan miss extended periods of formal schooling, creating a severe educational crisis [3]. This disruption exacerbates existing educational inequalities, leading to significant learning loss, psychological distress, and diminished future prospects for a generation lacking basic knowledge and skills [4]. Traditional educational approaches are often ill-equipped to meet the complex needs of these children, who possess distinct linguistic backgrounds, varying levels of prior learning, and unique emotional challenges [5]. The imperative for personalized learning an educational approach that customizes the learning experience to individual learners becomes paramount in such contexts [6]. Personalized learning offers a more efficient and enjoyable approach to re-engaging with education, as it adapts to a student's pace, learning preferences, and specific knowledge deficiencies [7]. In challenging environments, artificial intelligence (AI) has significant potential to revolutionize educational delivery. AI technologies including machine learning, natural language processing, and adaptive algorithms have demonstrated the capability to evaluate complex data, identify patterns, and make decisions that emulate human cognitive functions [8]. Recent advances in AI have made practical, scalable personalization feasible: models and systems that trace knowledge states, predict mastery, and sequence content in real time enable individualized learning trajectories at scale [9]. Knowledge tracing research encompassing both classical probabilistic models and contemporary deep-learning approaches has matured into a robust set of methods that can be integrated into tutoring engines to estimate mastery and recommend remediation or acceleration [10]. In education, AI can facilitate dynamic content adaptation, provide individualized feedback, and automate assessment, enabling a level of personalization previously unattainable at scale. Advancements in natural language processing (NLP) and large language models enhance systems' capacity to support multilingual learners, deliver contextualized explanations, and generate culturally relevant learning prompts and formative feedback [11]. This article proposes that strategically implemented AI can serve as an effective instrument for developing customized learning pathways to address the urgent humanitarian and developmental challenge of providing continuous education to Sudanese children. We aim to outline a comprehensive framework for such an AI-powered system, discuss its core components, highlight innovative adaptations for the Sudanese context, and analyze its potential impact and associated ethical considerations. Taken together, these developments motivate an AI-centered design for personalized learning for students with interrupted education in Sudan: systems that combine proven learner models, multilingual NLP, offline-capable delivery, community validation, and

an ethics-by-design approach provide a realistic pathway to accelerate catch-up learning [12]. In recent years, a growing body of work has pointed out that AI-supported personalization can be especially valuable in schools and programs that operate with very limited resources. One recurring finding from pilot studies is that adaptive systems not only help students raise their test scores but also give them more control over how they move through lessons by matching the pace and content to their existing knowledge and motivation [13]. For learners who have been displaced or whose schooling has been interrupted, this kind of flexibility is particularly important. In practice, such tools can offer a way to recover missed material, lower the chances of dropping out, and guide students back into structured learning through steady feedback and focused remedial support [14]. In countries where infrastructure is weak, educators and aid organizations have increasingly looked at mobile and offline AI tools as a practical way to keep lessons going. Researchers have observed that even small models, when designed to run on low-cost devices, are able to maintain basic learning support during long periods of poor or unstable connectivity—a situation that is common for many children in areas affected by conflict [15]. When paired with advances in multilingual natural language processing, these systems can also deliver lessons in local dialects or mother tongues, which helps students overcome the language barriers that so often block access to formal schooling [16]. Taken together, these features show how AI can be adapted in very concrete ways to sustain education in fragile environments. It is essential to recognize that technology alone is inadequate for the development of AI-driven educational systems. The trust and utilization of these systems by teachers and students are affected by judgments concerning student data, potential algorithmic biases, and the involvement of local communities [17]. Local stakeholders must be engaged from the outset to establish objectives, choose materials that address local requirements, and define metrics for success to ensure the sustainability of these initiatives over time [18]. This strategy illustrates that although AI can offer innovative strategies for customizing education, its efficacy in Sudan is dependent on both ethical considerations and societal acceptance, in addition to technical capability.

2. Literature Review

Artificial Intelligence in Education (AIEd) has a long history of integration and application. Artificial Intelligence in Education (AIEd) emerged in the early 1900s as a result of the convergence of learning theory and machine development. Initial activities in this domain concentrated on delivering tailored education, establishing the groundwork for subsequent advancements in AIEd [19]. Pressey and Skinner were pioneers in creating computers capable of autonomous student education, establishing a foundation for subsequent intelligent and adaptive teaching methodologies. With technological advancements and the capacity of artificial intelligence to replicate human cognitive functions, initial endeavors resulted in notable enhancements in the precision and customization of educational tools, thereby augmenting learning experiences and instructional quality across diverse educational environments [20]. Moreover, these advancements have initiated a transformation in educational methodologies by integrating innovative technologies with traditional teaching frameworks [21]. The implementation of AI in education (AIEd) has attracted considerable interest, with studies illustrating its promise in multiple areas of learning, such as intelligent tutoring systems, adaptive learning platforms, automated assessment, and tailored content recommendations [22]. A burgeoning body of research investigates AIEd in low-resource and crisis-affected situations, despite the preponderance of existing literature focusing on well-resourced educational environments. The primary objective of early AIEd initiatives was the creation of Intelligent Tutoring Systems (ITS) that replicate

human tutors by providing individualized education. By accommodating each learner's distinct growth and providing timely, targeted feedback, technologies such as Cognitive Tutor have proven efficient in enhancing student performance [23]. Recently, adaptive learning platforms utilize AI to modify the curriculum, pace, and instructional methods based on real-time student performance data, ensuring that learners are consistently challenged without being overwhelmed [24]. During crises, proactive, multidisciplinary collaboration and flexible decision-making are vital elements of effective educational leadership. Conventional top management methods, which are characterized by bureaucratic optimism and a lack of local response, are inadequate in times of crisis. As noted by some academics [25], proactive, multidisciplinary collaboration and flexible decision-making are vital elements of effective educational leadership during crises. A further component of strategic leadership in education is digital ethics and trauma-informed management. The employing of AI and digital surveillance techniques in conflict situations raises concerns about data privacy because these abilities may be accessible to authoritarian governments or other opposing sides Additionally, when faced with a crisis, leaders should be ready with relation to curriculum, educational methodology, and ethical decision making [26]. In contexts of educational disruption, the unique challenges necessitate specific AI applications. For example, because mobile phones are so widely available, even in distant locations, mobile learning, or m-learning, has become an essential delivery method [27]. Artificial intelligence can enhance mobile learning by facilitating offline material access, personalizing learning pathways according to device usage patterns, and optimizing content for compact screens. Natural Language Processing (NLP) facilitates interactive learning experiences via chatbots or voice assistants for students lacking access to human educators or preferring instruction in their native language [28]. Obstacles to implementing AIEd in low-resource environments encompass inadequate digital infrastructure, insufficient digital competence among learners and educators, and a deficiency of pertinent, localized digital material [29]. Moreover, privacy and data security are critical issues, particularly when engaging with vulnerable populations. Notwithstanding these obstacles, successful pilot initiatives in refugee camps and crisis areas have demonstrated the viability of technology-enhanced education [30]. These projects typically rely on community-based support, solar-powered systems, and offline functionalities [31]. This study expands upon these research findings by presenting an AI paradigm that emphasizes cultural relevance, flexibility, and accessibility to effectively navigate the intricate dynamics of the Sudanese setting.

3. Proposed System Architecture

The proposed AI-driven framework for personalized learning pathways in Sudan is designed to be modular, scalable, and adaptable to varying infrastructure levels and learner needs. It perceives learning as a dynamic interaction between the learner and an intelligent system that offers customized assistance, continually assesses performance, and adjusts information accordingly. We propose a modular architecture with three layers: (i) Data Collection (diagnostics, performance, engagement, contextual data), (ii) AI Processing (learner profiling, adaptive content engine, intelligent tutoring, analytics), and (iii) Learning Delivery (multi-platform interfaces, offline synchronization). The system iteratively personalizes learning paths and updates profiles from performance feedback. The fundamental architecture comprises three key layers: the learning delivery layer, the AI processing layer, and the data collecting layer. As illustrated in Figure 1, the system comprises three layers: data collecting, AI processing, and learning delivery. The Data Acquisition layer collects the learner's first evaluation, performance, engagement, and contextual data. The AI Processing layer utilizes machine learning algorithms to generate profiles for each student, transforming this data into actionable

insights. According to these profiles, the Intelligent Tutoring System provides customized feedback, while the Adaptive Content Engine selects and organizes the course materials. The Progress Tracking and Prediction Module utilizes predictive analytics to forecast future performance. The Learning Delivery Layer enables material dissemination across many devices by promoting interaction between the learner and the AI system.

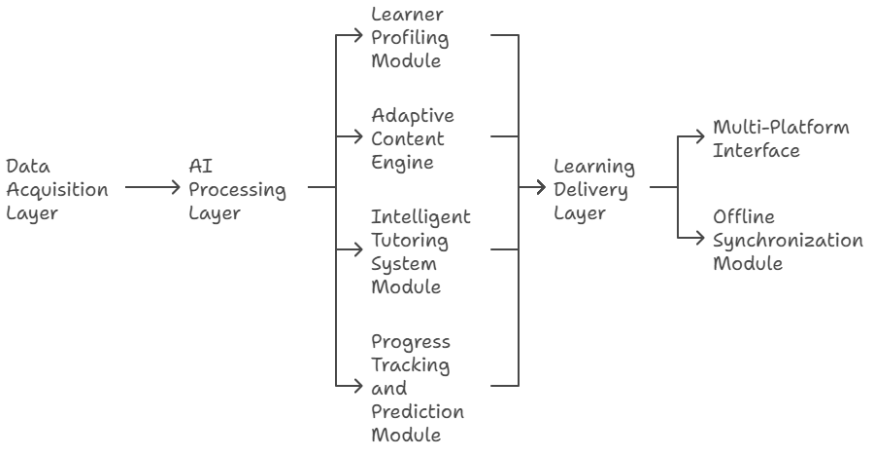

Figure 1. The core system architecture

Conceptual Flow (Pseudo-code).

FUNCTION PersonalizeLearningFor(learner_id):

1. Collecting_Data(learner_id) -> raw_data
2. Processing_Data(raw_data) -> learner_profile
3. Generating_Learning_Path(learner_profile) -> content_sequence
4. FOR EACH content_item IN content_sequence:
   a. Delivering_Content(content_item, learner_id)
   b. Monitoring_Performance(learner_id, content_item) -> performance_feedback
   c. IF performance_feedback indicates need for adjustment:
      i. Updating_Learner_Profile(learner_id, performance_feedback)
      ii. Adjust_Learning_Path(learner_id, learner_profile) -> new_content_sequence
      iii. iii. Continue with new_content_sequence
   d. IF learner requests for_help:
      i. Invoking_ITS(learner_id, current_concept) -> personalized_guidanceii. Delivering_Guidance(personalized_guidance)
5. Generating_Progress_Report(learner_id)

END FUNCTION

4. Components of the AI System

The suggested AI architecture comprises four primary components: Learner Profiling, Adaptive Content Delivery, Intelligent Tutoring Systems (ITS), and Interconnected Data. Learner Profiling employs diagnostic assessments, preliminary quizzes, and ongoing evaluations to ascertain knowledge deficiencies and strengths, along with a student's favored learning modalities and cognitive types. Adaptive Content Delivery ensures that appropriate content is provided to each student at the optimal time and in the most effective format. The system employs an extensive, modular store of educational resources, dynamic sequencing and recommendations, and multi-modal content adaption. Intelligent tutoring systems (ITS) provide personalized, human-like guidance

and feedback, encompassing dialogue systems, concept elucidations, sequential instructions, and problem-solving support. As illustrated in Figure 2, these components collaborate to form a highly tailored learning system. Information
from the delivery layer integrates with the ITS, adaptive content engine, and profile module.

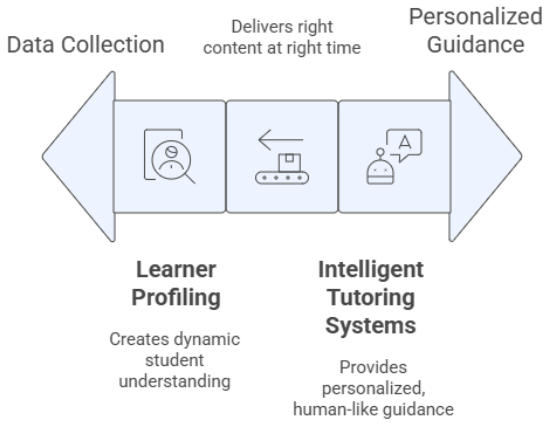

Figure 2. Components of AI System

To overcome specific logistical, cultural, and infrastructural challenges, the implementation of an AI-driven personalized learning system in Sudan necessitates not only technical expertise but also profound contextual understanding and innovative modifications. Given the extensive use of mobile phones in Sudan, it is essential to construct an AI-driven learning system. Students using low-end phones can access essential learning resources due to the system's capability to provide content via SMS or USSD. Students with low literacy or no literacy can benefit from the incorporation of voice-enabled learning. The system supports many languages and local dialects, features a multilingual content repository, and utilizes AI for localization and translation. Learning will persist irrespective of network availability through the utilization of offline-first models that employ opportunistic synchronization. Local server hubs serve as synchronization points for several devices and facilitate local content hosting. To ensure material is factual, relevant, and culturally appropriate, it must be validated and developed with community endorsement. To ensure cultural sensitivity and pedagogical integrity, it is imperative to engage local educators and elders in the assessment and validation of AI generated content. Figure 3 illustrates the strategies for enhancing education in Sudan.

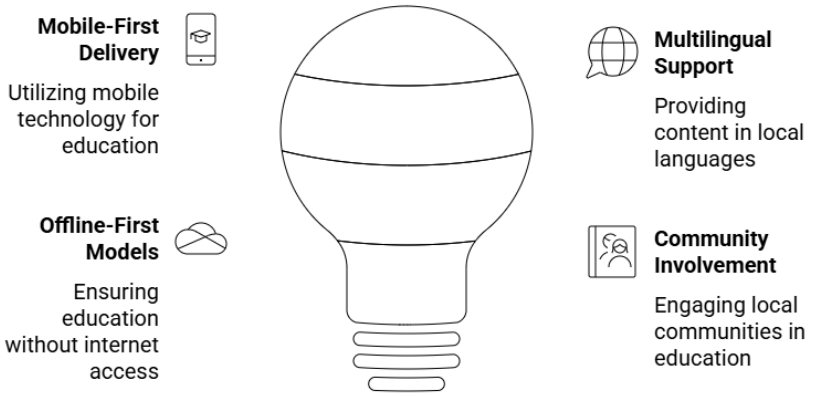

Figure 3. Enhancing education in Sudan

AI-powered individualized education will become a reality for those who need it most thanks to these creative strategies that aim to close the digital gap, get beyond language obstacles, and integrate the educational system into Sudanese communities' cultural norms.

5. System Implementation and Evaluation

The prototype system, Light of Learning–Personalized Learning for Every Student is an offline-first, AI-powered personalized learning system designed for students with interrupted education in Sudan. The system features a clean and responsive frontend, a multilingual platform, and two demo accounts for students and teachers. The core AI modules include AI-Powered Assessment, Smart Content Library, Knowledge Tracing, Offline-First Design, Recommendation Engine, Tutor Chat, and Stack Recap. The system allows students to onboard, take a diagnostic test, receive adaptive learning recommendations, and study offline, while teachers can upload content and monitor mastery. The system also includes a service worker. The backend uses Python 3.11+, Flask figure 4, SQLAlchemy, Flask-Login, and Flask-WTF, while the AI modules include MiniLM sentence-transformers, FAISS, and Bayesian Knowledge Tracing. The system also includes a pytest for authentication, BKT, and RAG integration. Figure 4 displays the main system interface.

The pilot study of the Light of Learning initiative will use a quasi-experimental design using a mixed-method approach, guided by a pretest/posttest methodology for about 12 weeks. It will involve 200-300 children aged 8-18 years with 2-5 years of disrupted schooling, and will randomly assign children to two groups through stratified random selection, one group receiving AI assistance and the other not. Performance measures will include grade equivalent gain, standardized subject tests, satisfaction surveys, qualitative interviews and system logs. Data will be collected in various ways. Ethical principles will be followed to ensure data is anonymized, stored securely and participants can withdraw at any time. The quantitative analysis will use paired t-tests, ANCOVA and effect calculation methods. Qualitative analysis will be based on thematic analysis. The project will be carried out over seven months, including the institutional review board approval, baseline testing, intervention, post-intervention phase, and finalization of the report.

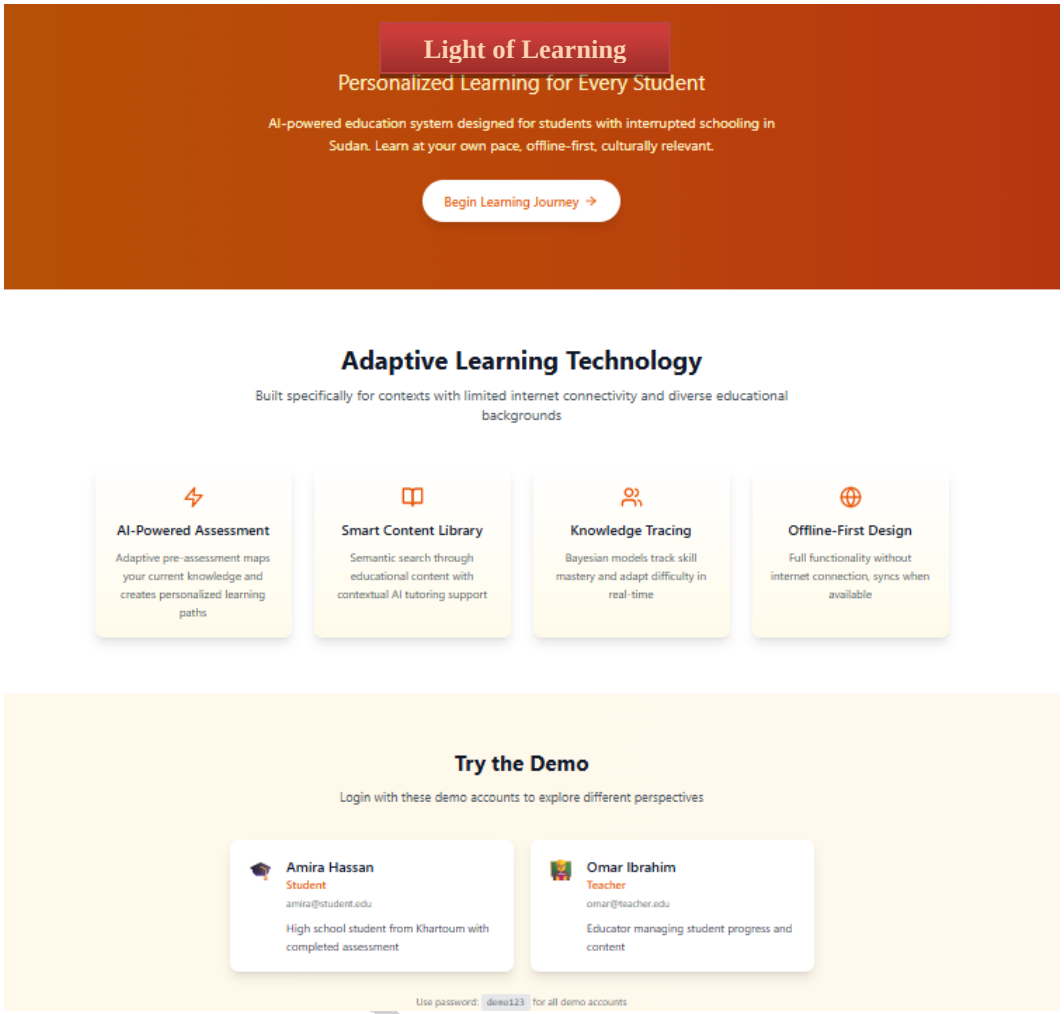

Figure 4: The system implementation

The Learning Light system's implementation allows educators to provide an interactive platform to supervise management their students' educational journeys. With the use of the system's simplified interface, instructors may see real-time student progress, levels of participation, and learning patterns. Light of Learning According to Figures 5 and 6 the system contributes to accessible, Student administration: Using a single interface, educators can add new students and monitor their development. Progress Monitoring: indicators of achievement like the last action timestamp, daily pattern, contribution rate, and progress percentage are displayed in each student profile.

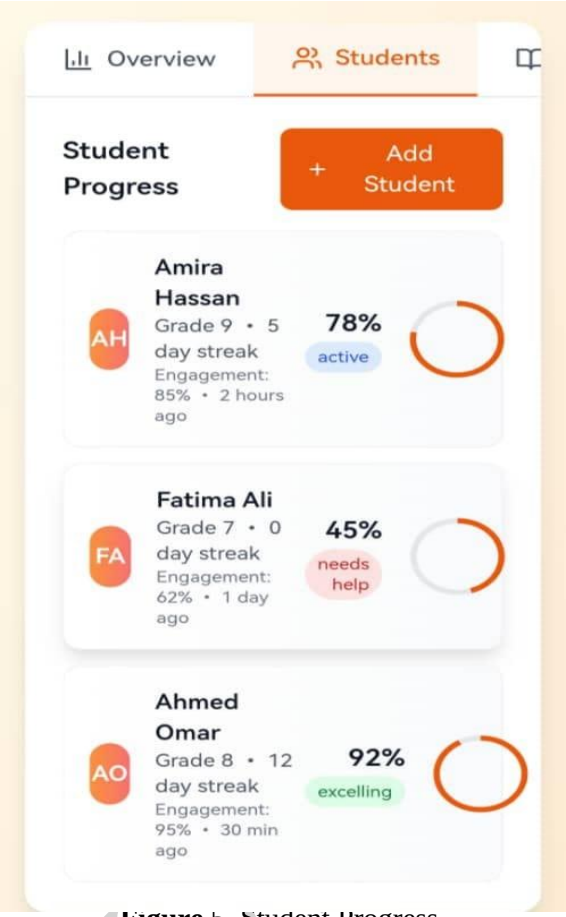

Figure 5. Student Progress

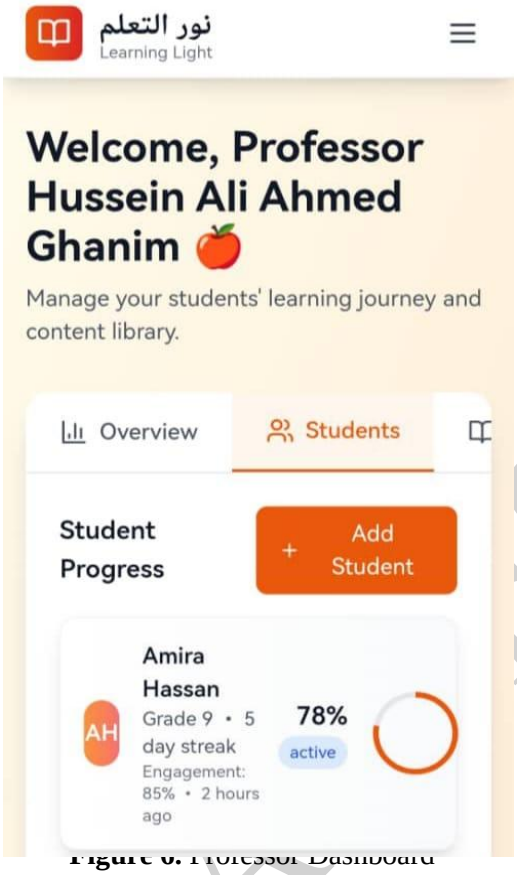

Figure 6. Professor Dashboard

6. Results and Discussion

To demonstrate the practical implementation and potential influence of the proposed AI-driven personalized learning system, consider a hypothetical deployment in a refugee camp in Eastern Sudan, accommodating thousands of displaced persons, many of whom are children and adolescents with disrupted education. The initiative aims to create a structured educational framework for 5,000 children and adolescents aged 8-18 who have experienced a 2–5-year interruption in formal schooling. The infrastructure includes a central community learning hub equipped with solar panels, a local server, and mobile device charging stations. A compact group of volunteer educators from the camp population receives training in fundamental digital literacy and system facilitation. The deployment phase encompasses initial evaluation, device allocation, tailored content dissemination, and community involvement and coordination. The technology can improve accessibility, accelerate learning, increase engagement, and provide essential data on learning patterns. Challenges encompass initial digital literacy, power and connectivity issues, content generation, and the continuous technical support and maintenance of devices and local server infrastructure. Possible effects include improved accessibility, accelerated learning, increased engagement, skill development, and data-driven insights. Challenges include foundational digital literacy, power and connectivity obstacles, content creation, and ongoing maintenance. The AI can enhance education for refugee children; Figure 7 illustrates the problems of AI-powered education in Sudan for these children.

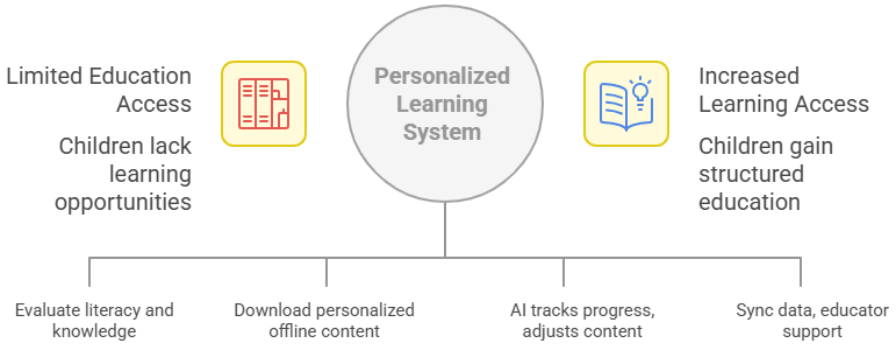

Figure 7. AI-Powered Education for refugee children

Notwithstanding these limitations, a meticulously crafted and contextually attuned AI-driven personalized learning system possesses significant potential to enhance educational outcomes for displaced and conflict-affected children in Sudan.
Existing literature on individualized learning and EdTech interventions in crisis contexts points to the Light of Learning system having potential for significant effects on accelerating learning, with effect sizes between 0.4 and 0.8 standard deviations. This means that students could close 1-2 grade level gaps in a year of consistent use. It is probable that engagement will increase and dropout rates decrease with the use of culturally sensitive and mobile first design with gamification features and personalised feedback. One prediction is that the offline-first architecture will allow 70-80% of learning interactions to occur without connectivity, thus ensuring continued access in remote areas. The teacher dashboards are designed to support the facilitators and spaced repetition strategies will support long-term knowledge retention. The modular design should also lend itself to future scaling. But a comprehensive future evaluation agenda will be needed to rigorously validate the expected outcomes and prepare for large-scale deployment including a randomized controlled trial to establish causal evidence of AI-driven personalization, longitudinal studies following cohorts for 18–24 months to validate real-world educational and employment transitions, scalability assessments with >5000 users, cross-context validation in other conflict-affected regions (e.g. Yemen or Syria), cost-effectiveness analyses comparing the system to traditional interventions, comparative effectiveness studies against non-AI models, online literacy impact assessments and sustainability analyses examining community ownership and government integration. These broad evaluation requirements are a major challenge outside the current framework, but are necessary for the credibility, effectiveness and long-term sustainability of the system. This proposed pilot study represents the crucial first step of this phased research agenda.

7. Analysis: Benefits, Limitations, Risks, and Ethics concerns

Benefits: access in remote settings; individualized pacing and remediation; engaging feedback; data-informed decisions.
Limitations: infrastructure dependency; digital literacy demands; localization overhead; maintenance.
Risks: algorithmic bias; over-reliance on technology; inequitable access; system failures.
Ethics: privacy/security (minimization, consent, encryption); fairness and cultural relevance; accountability and human-in-the-loop governance.
The deployment of AI for personalized learning in crisis-affected regions like Sudan presents a dual landscape of immense opportunity and significant challenges. A thorough analysis of its benefits, inherent limitations, potential risks, and critical ethical concerns is essential for responsible and effective implementation. AI-powered platforms can

provide enhanced accessibility and reach to students in remote areas, refugee camps, or conflict zones, bridging learning gaps and increasing engagement. They can analyze individual learning patterns, strengths, and weaknesses, tailoring content, pace, and instructional strategies for thousands of students simultaneously. AI can also identify knowledge gaps and provide targeted remediation, allowing students to catch up on missed learning more quickly. Adaptive content, interactive elements, and personalized feedback can make learning more engaging and less frustrating. Data-driven insights from AI systems can inform educators and policymakers, aiding in curriculum development, resource allocation, and intervention strategies. However, AI systems have limitations, including infrastructure dependence, digital literacy, content creation and localization, lack of human interaction, and maintenance and technical support. Risks include algorithmic bias, over-reliance on technology, exacerbation of the digital divide, and system failure and downtime. Ethical concerns include data privacy, security, equitable access, cultural relevance, accountability, and human agency. Ensuring data privacy, security, equitable access, cultural relevance, accountability, and human agency are crucial for the success of AI-powered learning. Figure 8 displays the features and limitations of using AI in education especially in Sudan.

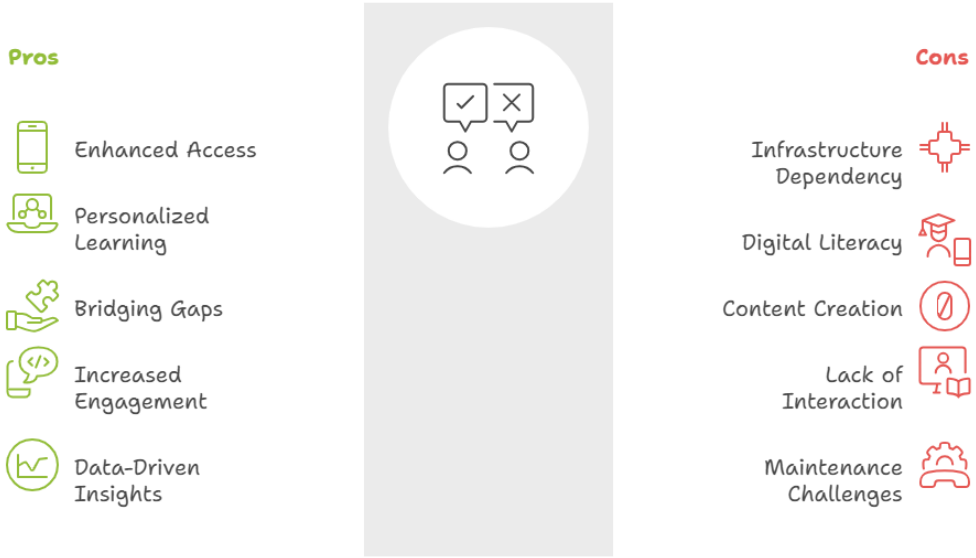

Figure 8. AI in Education Pros and Cons

Addressing these constraints and concerns by careful design, comprehensive policy, and ongoing stakeholder engagement is essential for realizing the full potential of AI in personalized learning in Sudan.

8. Conclusion and Future Work

The challenge of providing quality education to pupils with interrupted schooling in Sudan is considerable; nevertheless, the advent of Artificial Intelligence offers a unique and substantial opportunity to address this dilemma. This research presents a comprehensive AI-driven framework for personalized learning pathways, tailored to the unique complexities of the Sudanese context. This system employs adaptive content delivery, intelligent tutoring systems,
and dynamic learner profiling, in conjunction with strategies like mobile-first design, local dialect support, offline functionality, and community validation, to restore educational continuity and empower a generation of learners. The suggested implementation in a refugee camp illustrates the practical feasibility and transformative impact of this initiative, demonstrating how AI may rectify substantial educational

shortcomings, enhance participation, and provide widespread access to education when traditional institutions falter. However, the path forward is laden with challenges. Significant limitations regarding infrastructure, digital literacy, and content development must be resolved. Moreover, substantial risks such as algorithmic bias and overreliance on technology, together with critical ethical concerns about data privacy, equitable access, and cultural relevance, require comprehensive analysis and proactive mitigation strategies. Integrating AI into customized learning in crisis zones requires contextual awareness, hybrid models, robust offline capabilities, ethical AI design, and sustainable funding. Hybrid models amalgamate the customization capabilities of AI with the socio-emotional assistance offered by human educators. Lasting success requires sustained partnerships among governments, NGOs, technology providers, and local communities. Future research should focus on the advancement of open-source AIEd platforms, the implementation of empirical studies, and the exploration of innovative digital literacy teaching methods. Artificial intelligence can act as a crucial catalyst for educational equity and resilience in challenging circumstances.

The research agenda outlines ten priority areas for the development of AI-powered personalised education in crisis-affected regions, based on empirical validation in the proposed pilot study and later in large-scale RCTs and longitudinal research to confirm educational effectiveness. These include algorithmic fairness to identify and mitigate bias based on gender, ethnicity and socio-economic status; cultural adaptation through participatory design with local communities; and hybrid learning models that best combine AI-driven teaching with human teaching and socio-emotional support. The technical priorities are to optimize AI for offline use on low-cost devices through model compression and federated learning, and to develop natural language processing capabilities for under-represented languages such as Sudanese Arabic. Learning analytics research will focus on predictive models to identify at risk students and learning pathways. Policy and governance research will include data privacy, quality assurance and regulatory structures. Such sustainability models, with their emphasis on public-private partnerships and the inclusion of governments, dovetail with impact assessment frameworks that go beyond academic outcomes to encompass social and emotional wellness, community development, and long-term resilience. This ensures a comprehensive strategy that considers not only technical effectiveness but also the complex human aspects of education in humanitarian settings.

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