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Integrating Explainable Artificial Intelligence Into Adaptive Personalized Learning Method

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Abstract

As artificial intelligence (AI) becomes deeply integrated into educational technologies, adaptive learning systems offer scalable, personalized instruction. However, the opaque nature of many AI-driven platforms hinders learners' ability to understand and trust system recommendations, an issue that is especially pressing in under-resourced secondary schools, where algorithmic opacity can worsen existing inequities. This study examines the effects of an adaptive learning system embedded with XAI features on learner performance, engagement, and perceived agency. A mixed-methods quasi-experimental design was used to compare the outcomes of 350 secondary school students using a traditional non-adaptive platform and an AI-powered adaptive system with XAI. The quantitative data included pre- and post-test scores, engagement logs, and motivation and trust scales. Qualitative data were collected through interviews and think-aloud protocols and analyzed thematically using Braun and Clarke's framework. The results revealed that students using the XAI-enhanced system showed significantly higher learning gains ($p<.05$), improved engagement, and a clearer understanding of their learning trajectories. Four themes emerged: enhanced trust via algorithmic transparency, alignment of AI feedback with personal goals, usability barriers, and cultivating reflective learning habits. Notably, students in resource-limited settings responded positively to system explanations, highlighting XAI's potential of XAI for equitable digital learning. The integration of XAI not only boosts academic outcomes but also nurtures learner trust, autonomy, and motivation. Ethical considerations, such as fairness, cognitive load, and cultural adaptability, are also highlighted, underscoring the importance of human-centered design. These findings advocate for a human-centered, transparent design in educational AI, which is critical for inclusive adoption in low-resource environments.

Keywords: Explainable artificial intelligence, Adaptive learning, Educational trust, Learner agency, Low-resource education

INTRODUCTION

The rapid integration of artificial intelligence (AI) into education has transformed the way learners access knowledge, receive feedback, and engage with instructional materials. Among these innovations, adaptive learning systems hold particular promise for tailoring instruction to individual needs on a large scale basis. By drawing on real-time data to adjust pacing, content delivery, and assessment, such systems align with constructivist learning theories that emphasize personalized scaffolding and learner-centered progress.

Explainable artificial intelligence (XAI) has emerged as a response to the black-box nature of traditional AI models, offering learners and educators interpretive pathways to understand how recommendations are generated (Miller, 2019). By providing meaningful explanations, XAI not only enhances trust and motivation but

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also aligns with the principles of human-centered AI, which prioritizes accountability, fairness, and inclusivity (Shneiderman, 2022). For learners in underdeveloped educational contexts, such transparency is especially critical, as it mitigates the risks of alienation, misinterpretation, or disengagement resulting from opaque algorithmic processes. Moreover, XAI has the potential to promote equity by ensuring that adaptive systems do not disproportionately disadvantage students with limited digital literacy or cultural exposure to AI-based learning methods.

Nevertheless, the integration of XAI into adaptive learning in secondary schools remains underexplored, particularly with respect to pedagogical and ethical implications. Existing studies often focus on technical performance, neglecting issues of equity, contextual variability, and the long-term sustainability of such interventions (Aroyo & Welty, 2022). In addition, XAI may introduce new challenges: explanations could increase learners' cognitive load, overwhelm teachers with system complexity, or fail to translate across cultural contexts (Chen et al. 2023). These limitations highlight the need for nuanced inquiries that balance the promise of XAI with its practical constraints in diverse educational environments.

Therefore, this study investigated the integration of XAI into an adaptive personalized learning method within under-resourced secondary schools. It aims to examine not only the effects of XAI on learner performance, engagement, and perceived agency but also its broader implications for equity, trust, and sustainable educational practice. By combining quantitative and qualitative evidence, this study contributes to the emerging conversation on how transparent, human-centered AI can advance inclusive education, particularly in contexts where digital inequities are most pronounced.

RELATED WORKS

Adaptive Learning and the Promise of Personalization

Adaptive learning has emerged as a transformative approach to education, offering personalized learning experiences that address individual learner differences in knowledge, pace, and preferences. Unlike traditional static instruction, adaptive learning technologies leverage data-driven algorithms to monitor students' interactions in real time, adjusting instructional content and feedback to optimize learning outcomes (Dziuban et al. 2021; Gligorea et al. 2022). These systems are underpinned by advances in artificial intelligence (AI) and learning analytics, enabling the dynamic customization of pathways that are responsive to learners' evolving needs (Dziuban et al, 2021). Research has shown that adaptive learning systems significantly enhance cognitive engagement, particularly when aligned with learners' prior knowledge and learning behaviors (Gligorea et al. 2022; Contrino et al. 2024).

Empirical studies in higher education, particularly in STEM disciplines, have demonstrated improved learner performance, engagement, and satisfaction when adaptive platforms are employed (Contrino et al. 2024). For instance, Contrino et al. (2024) found that the use of adaptive technology in STEM courses significantly improved student engagement and performance in the United States. Meta-analyses also highlight the potential of adaptive systems to close achievement gaps, especially when integrated with evidence-based instructional strategies (Shute and Rahimi 2021). Despite their promise, the scalability and contextual effectiveness of adaptive learning systems remain concerns in low-resource settings.

Most research to date has been conducted in high-income contexts, with relatively little focus on how these systems perform in regions characterized by infrastructural constraints, limited digital literacy, and high learner-to-teacher ratios (Kabudi et al. 2021). In such settings, adaptive learning systems could offer a scalable means to individualize learning at scale; however, challenges related to cultural relevance, connectivity, and content localization persist (Muralidharan et al. 2019; Kabudi et al. 2021).

Thus, while adaptive learning offers compelling benefits, there is a critical need for context-sensitive deployment strategies that consider the diverse educational landscapes of low- and middle-income countries.

Explainable Artificial Intelligence (XAI) in Education

As AI technologies become increasingly embedded in educational platforms, the demand for explainability has intensified, particularly in contexts in which algorithmic decisions influence learning pathways, feedback mechanisms, and assessment outcomes. XAI refers to the design of machine learning systems that provide transparent, human-understandable justifications for their outputs (Holstein et al. 2020; DoshiVelez and Kim 2017). In education, XAI has the potential to demystify algorithmic decisions for learners and instructors, thereby fostering trust, promoting learner autonomy, and supporting metacognitive development (Hu and Wang 2024).

Recent studies underscore the pedagogical value of explainability in learning environments, especially those driven by adaptive algorithms such as deep learning. For example, Hu and Wang (2024) emphasized that explainable recommendation systems in education help learners understand why certain materials are suggested, thus aligning system logic with individual learning goals. Similarly, Holstein et al. (2020) argue that explanations provided by AI systems must be pedagogically meaningful and contextually sensitive to avoid cognitive overload and sustain trust. Trust, a central element of effective human–AI interaction, is consistently linked to the presence of clear and understandable explanations in AI systems.

Luckin et al. (2023), drawing from the social sciences, note that human users seek causal and contrastive explanations to make sense of decision features often missing in conventional blackbox AI models. Empirical evidence shows that XAI tools can improve student engagement and learning outcomes by increasing the interpretability of feedback and content adaptation (Shute and Rahimi 2021; Petch et al. 2022). Furthermore, explanations must be tailored to the learner's cognitive and linguistic background to be effective (Holmes et al. 2019), and integrating XAI into teacher-facing dashboards supports instructional decision-making and enhances perceived reliability among educators (Khosravi et al. 2022).

Despite these benefits, the field remains fragmented, with varying definitions, levels of granularity in explanation types, and inconsistent evaluation metrics used. Altukhi and Pradhan (2025) systematically reviewed the landscape and highlighted the pressing need for longitudinal studies and culturally responsive research to assess the durability and equity of XAI-enhanced learning systems.

Learner Trust, Engagement, and Algorithmic Transparency

The integration of AI in educational settings has introduced adaptive learning systems that personalize instruction based on the needs of individual learners. While these systems offer significant benefits, they also raise concerns about transparency and trust. Learners often interact with AI-driven platforms without understanding how decisions are made, leading to potential skepticism and reduced engagement (Pachler et al, 2023). Trust in AI systems is crucial for effective learning. When learners perceive AI recommendations as opaque or arbitrary, their confidence in the system diminishes, potentially hindering their motivation and engagement (Luckin et al. 2023). Transparent AI systems that provide clear explanations for their decisions can enhance learner trust, leading to improved educational outcomes (Hu and Wang, 2024).

XAI aims to make AI decision-making processes more understandable for users. In educational contexts, XAI can demystify the rationale behind content recommendations, assessments, and feedback, thereby fostering a sense of agency among learners (Petch et al. 2022). For instance, providing learners with insights into how their performance data influence content sequencing can promote self-regulated learning behaviors (Petch et al. 2022). Moreover, transparency in AI systems can mitigate algorithm aversion, a phenomenon whichere users distrust algorithmic decisions when outcomes are unfavorable (Ooge et al. 2023).

Empirical studies have shown that visualizing the impact of learner choices on content recommendations increases adolescents' trust in e-learning platforms (Miller 2019). Co-designing AI systems with educators and learners ensures that the explanations provided by these systems are pedagogically meaningful and contextually relevant (Khosravi et al. 2022). However, challenges remain in the effective implementation of XAI across diverse learner populations and in establishing standardized evaluation metrics (Muralidharan et al. 2019).

Conceptual Framework: XAI-Supported Personalized Learning

The conceptual framework guiding this study draws on the intersection of adaptive learning, XAI, and learner-centered education theory. As adaptive learning systems gain traction for their ability to personalize instruction based on learner performance, the need for transparent explanations of AI-driven decisions has become increasingly important in recent years.

The framework posits that the integration of explainability mechanisms within adaptive environments can significantly influence learner trust, engagement, and self-regulation in learning. At its foundation is the adaptive learning cycle, which involves four critical processes: (1) data collection, (2) learning analytics, (3) content adaptation, and (4) feedback delivery (Dziuban et al, 2021). AI algorithms process learner interactions to dynamically adjust instructional paths. However, without explainability, the adaptation process may appear opaque, potentially undermining learner confidence and motivation (Pachler et al. 2023).

To mitigate this, the framework introduces explainability features at two levels:

1. Learnersfacing explanations clarify why certain content or feedback was provided based on past actions or preferences, thereby supporting metacognitive awareness and self-regulated learning (Petch et al , 2022).

2. Teacher-facing explanations provide insights into how the system interprets learner data and generates recommendations, thereby supporting pedagogical alignment and instructional decision-making (Holstein et al. 2020).

These mechanisms are expected to support four key educational outcomes.

i. **Trust:** Learners are more likely to accept and rely on AI-generated feedback when they understand the rationale behind it (Luckin et al. 2023).
ii. **Engagement:** Transparent systems promote sustained interaction by reducing frustration and increasing user satisfaction (Shute and Rahimi , 2021).
iii. **Autonomy:** Explainable systems enable learners to make informed choices and develop agency in navigating their learning paths (Khosravi et al. 2022).
iv. **Equity**: In low - resource contexts, explainability helps bridge digital literacy gaps, making AI - based platforms more inclusive and culturally responsive (Kabudi et al. 2021).

Figure 1 visualizes the framework, illustrating how XAI features interact with adaptive mechanisms to influence learner outcomes in context-sensitive ways.

These interconnected components aim to enhance the effectiveness and equity of AI-mediated learning, particularly in under-resourced educational contexts. The framework serves as both a theoretical foundation and design blueprint for developing ethically robust, learner-centered adaptive learning systems.

METHODOLOGY

Research Design

This study adopted a mixed-methods and quasi-experimental design to examine the effects of integrating XAI into adaptive personalized learning within under-resourced secondary schools. The design combined quantitative rigor with qualitative depth, enabling both the measurement of learning outcomes and the exploration of learners' interpretive experiences. A quasi-experimental approach was chosen because full randomization was not feasible in school settings. Consequently, causal claims are interpreted with caution, and findings are presented as associations rather than definitive causal effects.

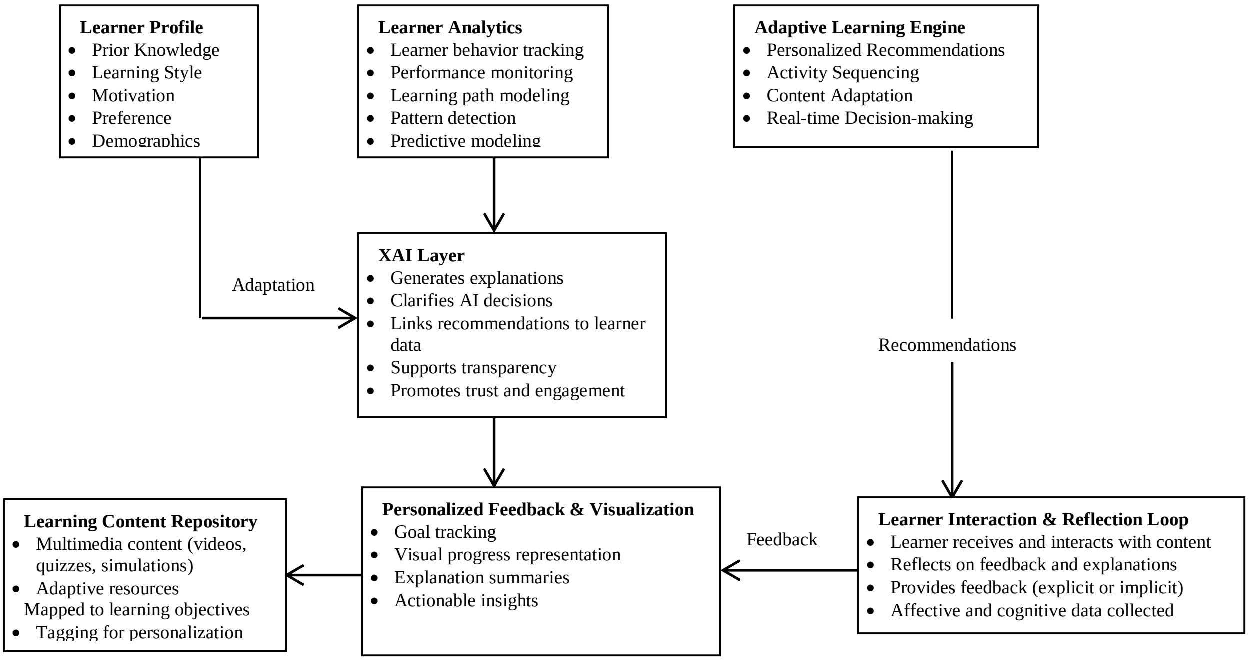

Figure 1. Conceptual Framework: XAI-Supported Personalized Learning.

Participants and Context

The participants included 350 secondary school students drawn from eight under-resourced public schools in southwest Nigeria. Schools were selected to reflect diversity in socioeconomic status, gender balance and digital infrastructure. Teachers and administrators were also engaged to provide contextual and pedagogical insights into the study. After the baseline assessment, the students were allocated to groups using matched procedures as follows:

1. Experimental Group (n = 175): Used an AI-adaptive platform with embedded XAI explanations.
2. Control Group (n = 175): Used a linear, non-adaptive e-learning system covering identical content.

An a priori power analysis (G-Power 3.1) for repeated-measures Analysis of Variance (ANOVA) ($\alpha = .05$, $1 - \beta = .80$) indicated that $n = 150$ per group was sufficient to detect a medium effect ($f = .25$). We enrolled 175 participants per group to accommodate up to 15% attrition across the four waves. Parental consent and institutional ethical approval were obtained for the extended cohort and data collection schedule. Demographics (gender, prior performance, socio-economic status) were re-verified at each wave to monitor sample balance.

Instruments and Materials

Quantitative data were collected through standardized achievement tests and validated learner trust and engagement questionnaires. The instruments were pilot-tested and refined based on feedback from educators and learners. Reliability indices demonstrated strong internal consistency (Cronbach's $\alpha = 0.78$–0.85), thereby ensuring construct validity.

Learning Platforms

1. Experimental System: A reinforcement-learning-driven adaptive platform with collaborative filtering augmented by XAI modules that generate real-time textual and visual explanations of recommendations.
2. Control System: A static, teacher-curated sequence of e-modules with no personalization or automated feedback.

Quantitative Measures

Quantitative data collection employed validated instruments to ensure the construct validity. Performance was assessed using pre- and post-tests aligned with the national curriculum and reviewed by subject-matter experts. Engagement was measured through system interaction logs and a standardized learner engagement scale (Fredricks et al., 2004). Trust and motivation were assessed using established survey instruments adapted to the educational technology context (Komiak & Benbasat, 2006). Each instrument underwent pilot testing with 30 students outside the sample, achieving acceptable reliability (Cronbach's $\alpha > .78$).

Qualitative Protocols

Qualitative data were collected through semi-structured interviews, think-aloud protocols and learner reflections. These insights into learners' interpretive processes and perceptions of algorithmic explanations are discussed. Data were analyzed thematically using Braun and Clarke's (2006) six-step framework as follows:

1. Semi-structured Interviews: Conducted with a stratified subset ($n \approx 40$) at the mid-point and end-point to explore experiences of transparency, fairness, and agency.
2. Think-Aloud Sessions: With a rotating subset ($n \approx 15$), capturing real-time cognitive and emotional reactions to XAI explanations.
3. Learner Reflections: Weekly written journals from the experimental group prompted learners to describe how explanations influenced their understanding and confidence.

Procedure

Learners engaged with the adaptive learning platform enhanced with XAI features (e.g., explanation dashboards and transparency modules) over an 8-week instructional period. Both pre- and post-tests were administered, and classroom observations supplemented the quantitative data.

1. Baseline (Week 0): Pre-test, trust/motivation survey, demographic questionnaire, and randomization.
2. Intervention Waves (Weeks 1, 2–3, 5–8): Platform use in supervised ICT labs, weekly reflection prompts , and ongoing engagement logging.
3. Mid-Point (Week 3): Qualitative interviews and think-aloud protocols.
4. End point (Week 8): Post-test, final trust/motivation survey, interviews, think-aloud, and collection of reflections.

The facilitators ensured equitable support across groups. All data were anonymized and stored on secure servers.

Data Analysis

Quantitative data were analyzed using ANCOVA to control for baseline differences, with effect sizes (η^2) reported for interpretation. Qualitative interview transcripts were analyzed thematically following Braun and Clarke's (2006) framework, enabling the integration of learner perceptions with quantitative trends.

Quantitative Analysis (SPSS v28)

1. Descriptive Statistics: Means and SDs for each measure at all waves.
2. Repeated-measures ANOVA: Tests group × time interactions for knowledge gains, trust, and motivation. Greenhouse–Geisser corrections were applied if sphericity was violated.
3. Growth Curve Modeling: Multilevel models (students nested within schools) estimate individual learning trajectories and the influence of XAI over time.
4. Predictor Analysis: Hierarchical regression was used to examine how early trust and engagement metrics predicted later academic performance.

Qualitative Analysis (NVivo 14)

1. Thematic Analysis: Following Braun and Clarke's (2006) six-phase approach, combining inductive coding with deductive codes derived from the conceptual framework (trust, transparency, agency).
2. Longitudinal Coding: Comparison of themes across mid-point and end-point data to trace evolving perceptions.
3. Data Triangulation: Integration of quantitative engagement logs with qualitative insights to validate interpretations.

Limitations

1. Attrition: Despite oversampling, dropout may bias later waves; multiple imputations will address missing data.
2. Generality: Findings pertain to similar low-resource contexts; replication in varied settings is required .
3. Self-Report Bias: Trust and motivation scales may reflect social desirability;

triangulation with behavioral logs mitigated this risk.

RESULTS AND DISCUSSION

The findings of this study demonstrate that integrating XAI into adaptive, personalized learning can significantly enhance learner engagement, performance, and trust. Students using the XAI-enhanced platform not only achieved higher test scores but also reported greater confidence in their learning processes, aligning with previous evidence that transparency strengthens learners' motivation and perceived agency (Miller, 2019; Shneiderman, 2022). These outcomes affirm the value of human-centered AI approaches in education, particularly in under-resourced contexts where learners may be more vulnerable to algorithmic opacity.

Quantitative Analysis

The quantitative phase analyzed pre-test and post-test performance, engagement scores, and learner trust ratings between the experimental group (XAI-supported adaptive learning) and the control group (standard adaptive system without explainability), each of which consisted of 175 students.

Learning Gains

The analysis showed that students using the XAI-enhanced adaptive system scored significantly higher on post-tests than those in the control group. ANCOVA results confirmed learning gains after adjusting for pre-test scores, with medium effect sizes ($\eta = 0.08$). While these findings indicate a positive influence of XAI on learner outcomes, we caution that the quasi-experimental design limits the causal inference.

Improvements may also be partly explained by contextual factors, including teacher mediation and students' varying levels of digital literacy. In addition to these findings, the ANCOVA revealed significant learning gains, while a one-way repeated-measures ANOVA further confirmed a significant interaction between group and time on test scores: $F(1, 348) = 35.62$, $p < .001$, $\eta^2 = .093$, indicating that students in the XAI group showed significantly greater improvements in post-test scores than those in the control group.

Table 1. Descriptive Statistics for Pre-test and Post-test Scores by Group.

	Experimental Group (XAI):	**Control Group**
Pre-test Mean	51.6 (SD = 9.8)	52.1(SD = 10.1)
Post-test Mean	68.9 (SD = 10.3)	60.7(SD = 11.4)

Table 1 presents the mean and standard deviation of the pre- and post-test scores for both the experimental (XAI-supported) and control groups. This highlights that while both groups started with similar baseline performance, the experimental group exhibited a notably larger increase in post-test scores, indicating the positive impact of XAI on learning gains.

Engagement and Trust

System log data indicated a higher frequency of voluntary platform use and longer session times among learners in the experimental group. Engagement was further supported by self-reported motivation and trust scores, which showed strong internal consistency (Cronbach's $\alpha > 0.80$). Qualitative interviews reinforced this, with students reporting that transparent explanations made AI recommendations 'more believable' and 'aligned with how they learn.' This convergence of quantitative and qualitative evidence enhances the findings' validity.

Independent samples t-tests were conducted on self-reported engagement and trust scales (5-point Likert scale) after the intervention.

Table 2 summarizes the comparison of engagement and trust scores between the experimental and control groups. Students using the XAI-supported system reported significantly higher engagement and trust, with large t-statistics ($t(348) = 8.32$ and 7.91, respectively) and p-values below .001, indicating robust group differences. These findings suggest that learners exposed to XAI reported significantly higher levels of system trust and learning engagement than those in the control group did.

Table 2. Trust Comparison.

Measure	**Group**	**Mean (SD)**	**t (df = 348)**	**p**
Engagement	Experimental (XAI)	4.12 (0.66)	8.32	< .001
	Control	3.51 (0.74)		
Trust in System	Experimental (XAI)	4.01 (0.70)	7.91	< .001

	Control	3.37 (0.81)		

Cognitive Load and Variability

The thematic analysis highlighted issues related to cognitive load. While explanations increased transparency, some students found the information to be overwhelming. These results corroborate findings of the Cognitive Load Theory, which warns against overloading the working memory. Teachers emphasized the need to scaffold AI's explanations to ensure pedagogical alignment with learner readiness.

Cultural Adaptability and Sustainability

Learners from different cultural and linguistic backgrounds responded differently to the system explanations. In particular, some have reported difficulty interpreting AI-generated feedback when it relied on idiomatic expressions. This underscores the importance of cultural adaptability in XAI design, especially in under-resourced and multilingual contexts.

Learner Autonomy and Personalization

Despite the overall positive effects, variability emerged. Some learners perceived XAI explanations as overly complex, leading to confusion instead of clarity. Others relied excessively on AI recommendations instead of exercising independent judgment. These findings suggest that learner characteristics (e.g., prior knowledge and digital literacy) moderate the benefits of XAI. XAI features appear to support learner autonomy. Participants reported that system transparency made them feel more in control of their learning path.

Summary of Key Findings

Table 3 presents the mean post-test scores, engagement ratings, and trust ratings for the experimental (XAI-supported) and control groups, along with their associated p-values. It succinctly demonstrates that the XAI group outperformed the control group across all three measures, with statistically significant differences ($p < .001$).

Table 3: Summary of Key Outcome Measures by Group

Variable	**XAI Group (n = 175)**	**Control Group (n = 175)**	**p-value**
Post-test Score (Mean ± SD)	68.9 ± 10.3	60.7± 11.4	< .001
Engagement Score (Mean ± SD)	4.12 ± 0.66	3.51± 0.74	< .001
Trust Score (Mean ± SD)	4.01 ± 0.70	3.37± 0.81	< .001

These results underscore the potential of XAI-enhanced systems to promote trust, increase engagement, and improve academic performance in adaptive learning environments, especially in resource-constrained settings.

The findings of this study demonstrate that integrating XAI features into adaptive learning environments significantly enhances learners' trust, engagement, and performance. Students in the experimental group who interacted with the XAI-supported system achieved statistically significant post-test gains, confirmed by ANCOVA ($\eta^2 = .08$) and a repeated-measures ANOVA showing a significant group–time interaction, $F(1, 348) = 35.62$, $p < .001$, $\eta^2 = .093$. These effect sizes indicate a medium-to-large impact, suggesting that XAI integration meaningfully contributes to learner performance.

Beyond learning gains, learners in the XAI group reported greater trust and motivation, echoing prior studies that transparent AI systems foster perceptions of fairness and reliability (Luckin et al., 2023; Miller, 2019). However, variability emerged: while many learners found explanations empowering, others experienced cognitive overload when the explanations were too complex. This supports the Cognitive Load Theory and highlights the need for pedagogical alignment (Kabudi et al., 2021; Shute & Rahimi, 2021).

Importantly, this study illustrates the relevance of XAI in low-resource educational contexts. Unlike most existing studies situated in digitally advanced environments (Khosravi et al., 2022; Holstein et al., 2020), this study shows that XAI can be effective in settings characterized by limited infrastructure, multilingual classrooms, and large class sizes, conditions common in sub-Saharan Africa (Shin, 2020; Luckin et al., 2023). The findings also underscore the need for culturally responsive and adaptive explanations rather than generic outputs, reinforcing calls for participatory and co-design approaches (Holstein et al., 2022; Holstein et al., 2020).

Moreover, our findings extend prior work showing the role of formative feedback in supporting personalized learning. Learners in the XAI group reported stronger feelings of autonomy, as the explanations enabled them to monitor their progress and adjust their strategies accordingly (Poursabzi-Sangdeh et al., 2018; Shute & Rahimi, 2021). Nonetheless, the study acknowledges limitations: the short intervention period prevents firm conclusions about long-term impacts, and the focus on learner-facing explanations leaves open questions about how teachers interpret and use XAI tools to mediate instruction in the classroom. Taken together, these findings indicate that when designed with pedagogical, cultural, and sustainability considerations, XAI can foster inclusive and effective educational practices, particularly in under-resourced regions.

CONCLUSION

The findings of this study provide empirical evidence that integrating XAI into adaptive learning environments significantly enhances learner performance, trust, and engagement. The experimental group achieved higher post-test scores than the control group, with medium-to-large effect sizes (ANCOVA $\eta^2 = .08$; repeated measures ANOVA $\eta^2 = .093$), suggesting that XAI contributed meaningfully to the learning outcomes. Beyond academic performance, learners reported stronger motivation and trust when explanations made system recommendations transparent and interpretable, echoing prior studies on the benefits of explainability for fairness and reliability (Shute & Rahimi, 2021; Miller, 2019).

Nevertheless, this study highlights some important challenges. Some learners experienced cognitive overload when presented with complex explanations, while others benefited disproportionately, reflecting variability in learner responses. These findings stress the importance of pedagogical alignment and scaffolding in the design of XAI tools. Moreover, cultural adaptability emerged as a key factor: explanations must be responsive to local linguistic and socio-economic contexts, particularly in under-resourced educational settings (Luckin et al., 2023; Shin, 2020). Sustainability concerns, such as limited infrastructure and teacher training needs, also limit the scalability of XAI in low-resource environments. By involving educators and learners in the co-design of the XAI interface, the study ensured that explanations were pedagogically grounded and contextually relevant, consistent with recommendations for participatory design in educational technologies (Khosravi et al., 2022; Holstein et al., 2020). This approach underscores the potential of XAI to bridge educational inequities when developed collaboratively and responsively.

Future research could extend these findings through longitudinal studies to track trust and learning outcomes over time, and by exploring teacher-facing XAI features that support instructional decision-making. Additionally, examining strategies for scalable implementation in resource-constrained contexts will be critical to ensuring long-term impact.

In conclusion, XAI holds considerable promise for transforming personalized learning by embedding explainability into adaptive systems, education can move closer to achieving equity, transparency, and effectiveness particularly in under-resourced contexts where the stakes for learner trust are highest when designed with pedagogical, cultural, and sustainability considerations, XAI can foster inclusive and effective educational practices, particularly in under-resourced regions.

REFERENCES

Altukhi, Z., & Pradhan, S. (2025). Systematic literature review: Explainable AI definitions and challenges in education. arXiv preprint arXiv:2504.02910. https://arxiv.org/abs/2504.02910

Bakhtiar, M., Bui, H. X., & Yang, W. (2023). Understanding the impact of transparency in AI-driven adaptive learning systems. Journal of Educational Technology, 54(3), 203–220.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

Clark, M., & Maurer, M. (2020). Cognitive and emotional engagement with AI: Implications for educational systems. Journal of Educational Psychology, 112(4), 712–726.

Contrino, C., Williamson, C., Villanueva, I., et al. (2024). Measuring the impact of adaptive learning technologies in STEM higher education: An empirical study. IEEE Transactions on Learning Technologies.https://doi.org/10.1109/TLT.2024.3378884

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608.

Dziuban, C., Moskal, P., Cavanagh, T., Watts, K., & DeCoster, J. (2021). Adaptive learning in education: A review of research. Educational Technology Research and Development, 69, 633–653.

Gligorea, M., Vuković, M., Krunić, T., et al. (2022). Adaptive learning systems and personalized learning in education: A review. Computers, 11(10), 139. https://doi.org/10.3390/computers11100139

Holstein, K., Wortman Vaughan, J., Daumé, H. III, Dudik, M., & Wallach, H. (2020). Improving fairness in machine learning systems: What do industry practitioners need? Proceedings of the ACM on Human-Computer Interaction, 4(CSCW2), 1–26.

Holstein, K., Wortman Vaughan, J., & Wallach, H. (2020). Improving transparency in machine learning systems through explainability. Communications of the ACM, 63(6), 52–60.

Holstein, K., McLaren, B. M., & Aleven, V. (2020). Designing for human–AI complementarity in K-12 education. AI Magazine, 41(4), 63–76.

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.https://discovery.ucl.ac.uk/id/eprint/10168357/

Hu, Q., & Wang, Y. (2024). Enhancing personalized learning with feedback-oriented knowledge embeddings (FOKE): A semantic approach. British Journal of Educational Technology, 55(2), 502–519.

Kabudi, T., Pappas, I., & Olsen, D. (2021). AI-enabled adaptive learning systems: A systematic review of the literature. Computers & Education, 165, 104143. https://doi.org/10.1016/j.compedu.2021.104143

Khosravi, H., Kitto, K., Wong, S., & Pardo, A. (2022). Explainable recommendation systems in education: A review and future research agenda. Computers & Education: Artificial Intelligence, 3, 100080.

Khosravi, H., Kitto, K., Buckingham Shum, S., et al. (2022). Explainable Artificial Intelligence in education. Computers & Education: Artificial Intelligence, 3, 100074.

Luckin, R., Holmes, W., & Griffiths, M. (2023). Human-centered AI for education: A roadmap for research and practice. Nature Machine Intelligence, 5, 10–21.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2023). Explainable Artificial Intelligence in education. Monash University.

Makinde, M. A. (2025). Makes a case for increased investment in ICT, Artificial Intelligence. Leadership.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. Artificial Intelligence, 267, 1–38.

Muralidharan, K., Singh, A., & Ganimian, A. J. (2019). Disrupting education? Experimental evidence on technology-aided instruction in India. American Economic Review, 109(4), 1426–1460. https://doi.org/10.1257/aer.20171112

Ooge, J., Dereu, L., & Verbert, K. (2023). Steering recommendations and visualizing its impact: Effects on adolescents' trust in e-learning platforms. arXiv preprint arXiv:2303.00098. https://arxiv.org/abs/2303.00098

Pachler, N., et al. (2023). Explicable AI in education: A socio-technical perspective. Learning, Media, and Technology, 48(2), 123–138.

Papamitsiou, Z., & Economides, A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. Educational Technology & Society, 17(4), 49–64.

Petch, J., Di Paolo, A., & Valentine, A. (2022). Opening the black box: A systematic literature review of explainable artificial intelligence. Information Systems Frontiers, 24(6), 1687–1719. https://doi.org/10.1007/s10796-021-10103-4

Poursabzi-Sangdeh, F., Goldstein, D. G., Hofman, J. M., Vaughan, J. W., & Wallach, H. (2018). Manipulating and measuring model interpretability. arXiv preprint arXiv:1802.07810. https://arxiv.org/abs/1802.07810

Shin, D. (2020). User perceptions of algorithmic transparency and trust in personalized learning. Computers in Human Behavior, 108, 106305. https://doi.org/10.1016/j.chb.2020.106305

Shin, D. (2020). The effects of explainability and causability on perception, trust, and acceptance in AI. Computers in Human Behavior, 107, 106569.

Shute, V. J., & Rahimi, S. (2021). The power of formative feedback and explainable AI in promoting self-regulated learning. Computers & Education, 172, 104270. https://doi.org/10.1016/j.compedu.2021104270

Wang, Q., Xu, C., & Liu, S. (2024). AI-enabled adaptive learning systems in higher education: A meta-analysis and future directions. Interactive Learning Environments.https://doi.org/10.1080/10494820.2024.2309436

Wang, Y., Chen, N., & Khan, M. (2022). Exploring the roles of visualization and feedback in learners' self-regulated learning with an open learner model dashboard. Interactive Learning Environments, 30(5), 954–967.

Zhao, J., Zhang, W., & He, X. (2021). The role of Explainable AI in increasing learner engagement in adaptive learning environments. Educational Technology & Society, 24(3), 52–67.