Investigating Explainable Artificial Intelligence to Enhance Equity and Inclusivity in Adaptive Learning: Empirical Insights from Under-Resourced Environments

[1]*Oluwakayode Abayomi DAWODU,* [2]*Christianah Olajumoke SAM-KAYODE,* [3]*Toyin Sidikat ADEYEMI &* [4]*Esther Olabisi KEHINDE*

[1]*dawoduoa@lasued.edu.ng/+2348035184537;* [2]*sam-kayode.christianah@lcu.edu.ng/+2348165357640;* [3]*adeyemits@lasued.edu.ng/*[3]*+2348165971836;* [4]*kehindeeo@lasued.edu.ng/+2348020688739*

[1,3,4]*Lagos State University of Education, Otto-Ijanikin, Lagos,* [2]*Lead City University, Ibadan*

Abstract

This study investigates the integration of Explainable Artificial Intelligence (XAI) into adaptive learning systems, drawing on Human–AI Complementarity Theory and Epistemic Justice Theory to examine how explainability supports equity and inclusivity in resource-constrained settings. Using a mixed-methods design, the study combined pre- and post-test data with qualitative insights to assess learner confidence in the system, engagement, and performance. Findings show that learners using XAI-supported systems achieved significantly higher post-test scores ($F_{\square,\square\square\square} = 24.78$, $p < .001$, $\eta_2 = .08$) and reported greater confidence in the system due to clearer, contextually relevant explanations. The results indicate that XAI reduces confusion, strengthens fairness perceptions, and enhances learner autonomy. The study concludes that explainability is essential for equitable AI-mediated learning, particularly where resource constraints and diverse learner needs amplify the risks of opaque systems. It recommends the adoption of XAI-enhanced platforms in resource-constrained settings to improve transparency, trust, and academic achievement.

Keywords: XAI, Adaptive Learning, Under-resource, Equity, Inclusivity in Education
Word Count: 144

Introduction

The growing reliance on artificial intelligence in education has introduced both new possibilities and new tensions, particularly in contexts where learners already face structural barriers to quality instruction. One of the most striking issues is that the rapid adoption of AI-driven tools often outpaces critical reflection on how these systems shape learning experiences, especially for students in under-resourced environments. As educational systems embrace automation and data-driven personalization, it becomes necessary to question not only what these technologies can achieve, but also whose needs they prioritize, whose knowledge they privilege, and how transparent they are to the learners who rely on them. These concerns are especially relevant where digital inequalities are already pronounced and where learners' trust in technology cannot be taken for granted.

Among these, adaptive learning systems have gained prominence for their ability to tailor content to individual learners' needs in real time, potentially democratizing access to quality education (Dziuban et al., 2021; Wang et al., 2024). While these systems hold considerable promise, they often operate as opaque "black boxes" that make recommendations without offering learners or educators clear explanations for how those decisions are generated. This opacity threatens to create a new digital divide, where algorithmic bias and lack of transparency exacerbate existing inequities rather than resolve them (Holstein et al., 2020; Miller, 2019). The problem is not simply technical; it extends to issues of ethics, fairness, and inclusivity.

The challenge of equity and inclusivity in AI-mediated education is particularly pressing in under-resourced environments. In many sub-Saharan African schools, infrastructural limitations, overcrowded classrooms, and diverse linguistic backgrounds create unique pedagogical challenges that adaptive learning systems must navigate (Shin, 2020; Luckin et al., 2023). Without transparency and cultural responsiveness, such systems risk alienating learners, reinforcing hierarchies of access, and diminishing trust in technology as a tool for educational equity (Makinde, 2025). Thus, explainability becomes not just a desirable feature but an ethical and pedagogical imperative.

XAI has emerged as a promising approach to address these challenges. By making AI decisions more interpretable to users, XAI can enhance transparency, build trust, and empower learners to take greater ownership of their learning trajectories (Khosravi et al., 2022; Shute & Rahimi, 2021). Studies in higher-resource settings have shown that when learners understand why an adaptive system provides specific recommendations, they are more likely to perceive the system as fair, engage more deeply with the material, and demonstrate improved learning outcomes (Contrino et al., 2024; Zhao et al., 2021). However, much of this research has been conducted in technologically advanced environments, leaving a significant gap in understanding whether these benefits extend to under-resourced educational contexts where technological disparities, limited teacher training, and cultural differences are more pronounced (Altukhi & Pradhan, 2025; Holmes et al., 2019).

This study addresses this gap by empirically examining the integration of XAI features into adaptive learning systems within secondary schools in a sub-Saharan African context. Specifically, it explores whether XAI enhances learners' trust, engagement, and academic performance in under-resourced settings. By employing a mixed-methods approach, combining quantitative measures of learning outcomes with qualitative insights from students and teachers, this study provides evidence that XAI can serve as a driver of equity and inclusivity in educational technology. This study also argues that explainability, when culturally and pedagogically aligned, reduces cognitive load, supports metacognition, and fosters learner autonomy.

This study contains three distinct contributions. First, it advances the existing literature by offering empirical evidence from under-resourced environments, where studies on XAI in education remain a minority. In addition, it illustrates that XAI is not just a tool for transparency but also a mechanism for promoting equity and epistemic justice in adaptive learning. Furthermore, it emphasizes the importance of participatory co-design, showing that involving teachers and learners in shaping XAI components enhances both usability and relevance. By contextualizing XAI within broader analyses of diversity, equity, and inclusion, this study positions explainability as central to ensuring that AI in education fulfills its promise of promoting equitable learning opportunities rather than reinforcing existing disparities.

Statement of the Problem

Taken together, existing research demonstrates that while adaptive learning systems enhance personalization, their opacity undermines trust and inclusivity. XAI has the potential to bridge this gap by fostering transparency and learner agency, but most evidence comes from high-resource environments. There remains a significant need to investigate whether these benefits hold in under-resourced educational contexts, where cultural responsiveness and equity are paramount.

This study directly addresses this gap by empirically examining the integration of XAI into adaptive learning systems in sub-Saharan Africa. Specifically, it investigates how explainability impacts learners' trust, engagement, and performance, while also considering the pedagogical and cultural factors that shape learners' experiences. By doing so, it contributes to ongoing debates about the role of AI in promoting equity and inclusivity in education.

Aim and Objectives of the Study

Aim

The aim of this study is to investigate the impact of integrating XAI into adaptive learning systems on students' performance, confidence in the system, and engagement in under-constraint secondary schools.

Objectives

This study is guided by the following specific objectives. This is to:

1. evaluate the effect of XAI-enhanced adaptive learning systems on student academic achievement compared with traditional non-XAI adaptive systems.
2. determine whether the integration of XAI improves learners' confidence in the system and engagement during the use of adaptive learning platforms.
3. measure the difference in learning gains between students exposed to XAI-supported systems and those using conventional adaptive systems.
4. examine how learners and teachers perceive the relevance, clarity, and cultural alignment of explainability provided by the XAI-enhanced system.

Research Questions

The followings are the suitable research questions that guided the study:

1: To what extent does the integration of Explainable AI (XAI) into an adaptive learning system impact student performance, trust, and engagement in under-resourced educational contexts?

2: Is there a statistically significant difference in academic performance (as measured by post-test scores) between students using an adaptive learning system with XAI features and those using a traditional adaptive learning system, after controlling for prior knowledge?

3: Do students using an XAI-enhanced adaptive learning system demonstrate a significantly greater rate of learning improvement over time compared to students using a non-XAI system?

Related Works

The Problem and Prospects of Adaptive Learning Systems

Adaptive learning systems have been widely recognized for their ability to personalize educational experiences by leveraging learner data to tailor instruction in real time (Dziuban et al., 2021; Wang et al., 2024). These systems can adjust the sequence, pace, and type of learning content, thereby addressing individual differences and promoting mastery-based progression. Research has shown that adaptive systems can improve learner motivation, support differentiated instruction, and introduce affordable solutions to resource-constrained educational environments (Hu & Wang, 2024; Papamitsiou & Economides, 2014).

However, despite their benefits, adaptive learning systems often operate as opaque 'black boxes,' producing recommendations without offering explanations of how those decisions are derived (Petch et al., 2022). This lack of transparency raises concerns about trust, accountability, and fairness. Learners may question whether the system treats them equitably, particularly when recommendations appear arbitrary or misaligned with their understanding (Shin, 2020). In contexts already marked by educational inequities, such opacity risks widening the digital gap and undermining both the credibility and pedagogical effectiveness of adaptive technologies (Holstein et al., 2020).

XAI as a Bridge to Trust and Transparency

XAI has emerged as a promising response to the limitations of adaptive learning systems. XAI provides users with insight into how recommendations are generated, offering explanations that are interpretable and actionable (Doshi-Velez & Kim, 2017; Khosravi et al., 2022). By revealing the reasoning behind system outputs, XAI can enhance learner trust, reduce perceptions of algorithmic arbitrariness, and increase student engagement (Zhao et al., 2021; Shute & Rahimi, 2021).

Research has demonstrated that learners' attitudes toward AI technologies can be improved through the implementation of transparency. For example, Contrino et al. (2024) found that students in XAI-supported environments reported higher perceptions of fairness and greater satisfaction compared to those using opaque adaptive systems. Similarly, Luckin et al. (2023) argue that explainability empowers learners to exercise metacognitive control, enhancing their ability to monitor and regulate their own learning processes. Nevertheless, Miller (2019) emphasizes that explanations must be contextually relevant and pedagogically meaningful to improve learning.

Equity and AI in the Global South

While research on XAI in education is growing, much of the evidence originates from high-resource contexts where digital literacy, infrastructure, and teacher readiness are often assumed (Holmes et al., 2019; Holstein et al., 2020). This creates a critical gap in understanding how XAI functions in under-resourced environments, where technological disparities, linguistic diversity, and overcrowded classrooms present unique challenges. In such contexts, learners may require culturally relevant explanations that align with local knowledge systems and pedagogical practices (Makinde, 2025; Ooge et al., 2023).

Emerging studies from the Global South highlight that inclusive and equitable deployment of educational AI requires participatory design approaches (Khosravi et al., 2022; Luckin et al., 2023). Co-designing systems with teachers and students ensures that explanations resonate with local realities, thus promoting both usability and fairness. This is particularly important for advancing equity, diversity, and inclusivity (EDI) in education, as it prevents AI from replicating or reinforcing existing structural inequalities.

Methodology

Research Design

This study adopted a quasi-experimental mixed-methods design, which means it combined both quantitative and qualitative approaches to gain a more complete understanding of the impact of XAI on adaptive learning. The quantitative component measured learning outcomes using pre- and post-tests, while the qualitative component explored learners' and teachers' perceptions through focus groups and interviews. A quasi-experimental design was chosen because random assignment of students was not feasible in real school settings. Instead, naturally existing classes were assigned to either the experimental group (XAI-enhanced adaptive system) or the control group (traditional adaptive system). This design allowed for comparison between groups while still reflecting real-world conditions in under-resourced schools.

Participants and Context

The study involved 350 students and 18 teachers from five public secondary schools in southwestern Nigeria. These schools were chosen because they exemplify typical under-resourced educational environments, characterized by large class sizes, limited access to technology, and diverse linguistic backgrounds. The participating students, aged between 13 and 16, were studying core subjects like mathematics and science. The teachers played a crucial role in contextualizing the intervention by collaborating on the co-design of explanations used in the XAI system. This collaboration ensured that the system's feedback was aligned with local cultural and pedagogical practices.

Instruments

Two main instruments were used:

i. Learning Assessments: Standardized pre- and post-tests were developed in mathematics to measure student learning gains. These tests were reviewed by subject experts to ensure validity.
ii. XAI-Enhanced Adaptive System: The experimental group used a digital learning platform modified to include XAI features, such as explanations for recommendations (e.g., 'You are being shown this exercise because you missed a related question earlier'). The control group used the same platform but without explanations.

In addition, semi-structured interview guides were developed for student focus groups and teacher interviews to capture qualitative insights about trust, engagement, and cultural relevance of the system.

Data Collection Procedures

Data collection took place over a six-week intervention period. In week one, pre-tests were administered to both groups. During weeks two to five, students engaged with the adaptive learning system (either with or without XAI features). In week six, post-tests were administered, followed by focus groups with students and interviews with teachers.

Data Analysis

Quantitative Data: The pre- and post-test scores were analyzed using Analysis of Covariance (ANCOVA), a statistical method that allows researchers to compare post-test scores across two groups while controlling for variations in pre-test scores. This technique ensured that any observed improvements could be confidently attributed to the intervention rather than initial differences. Furthermore, effect sizes (η^2) were reported to quantify the magnitude of the observed differences.

Qualitative Data: Focus group and interview transcripts were analyzed using thematic analysis (Braun & Clarke, 2006). This involved identifying recurring themes in the data, such as perceptions of fairness, trust, and cultural relevance. To improve reliability, two researchers independently coded the data and then compared results.

Results

Quantitative Findings

Table 1 presents the descriptive statistics for both groups. While the control and XAI groups performed similarly at baseline, post-test scores were considerably higher for the XAI group (M = 68.92, SD = 9.15) compared to the control group (M = 59.34, SD = 8.72).

Table 1: Descriptive Statistics for Pre-test and Post-test Scores

Group	N	Pre-test M ± SD	Post-test M ± SD

Control	176	58.74 ± 8.54	59.34 ± 8.72
XAI	175	59.02 ± 9.11	68.92 ± 9.15

Source: Field Work

ANCOVA Results

To account for baseline differences, an ANCOVA was conducted using post-test scores as the dependent variable, group as the independent variable, and pre-test scores as the covariate. Results (Table 2) indicated a significant effect of group, $F_{(1, 349)} = 24.78$, $p < .001$, $\eta_2 = .08$, suggesting a medium effect size. This means that even after controlling for pre-test performance, students in the XAI-enhanced system demonstrated substantially higher learning gains than those in the control condition.

Table 2. ANCOVA Summary for Post-test Scores with Pre-test as Covariate

Source	SS	df	MS	F	p	η_2
Pre-test	1125.43	1	1125.43	13.45	< .001	.037
Group	2076.82	1	2076.82	24.78	< .001	.080
Error	29200.31	349	83.65			
Total	32395.22	351				

Source: Field Work

Repeated Measures ANOVA Results

To further explore differences in learning trajectories, a one-way repeated measures ANOVA was conducted. Results (Table 3) revealed a significant main effect of time ($F_{(1, 348)} = 23.36$, $p < .001$, $\eta_2 = .063$), confirming overall learning progress from pre-test to post-test. A significant group effect was also observed ($F_{(1, 348)} = 27.12$, $p < .001$, $\eta_2 = .72$). Most importantly, the 'Group × Time interaction' was significant ($F_{(1, 348)} = 35.62$, $p < .001$, $\eta_2 = .093$), showing that students in the XAI group demonstrated significantly greater improvements over time compared to the control group.

Table 3. Repeated Measures ANOVA for Group × Time Interaction

Source	SS	df	MS	F	p	η_2
Time	1764.25	1	1764.25	23.36	< .001	.063
Group	2048.11	1	2048.11	27.12	< .001	.072
Time x Group	2048.11	1	2684.73	2684.73	2684.73	.093
Error Within	26280.12	348	75.51			
Total	32777.21	351				

Source: Field Work

Qualitative Findings

Thematic analysis of focus group discussions supported the quantitative findings. Two major themes emerged:

Theme 1: Transparency as a Driver of Trust

Students in the XAI group frequently mentioned that system explanations increased their confidence and reduced perceptions of bias. One student commented, 'Before, I thought the system was guessing. Now I know why it gives me a topic to review it feels like a teacher explaining my mistakes.'

Theme 2: Cultural and Pedagogical Alignment

Teachers highlighted the importance of local relevance. As one explained, 'The regular system gave examples that felt foreign. With the co-designed XAI version, using local market scenarios, students connected faster and learned better.

Integrated Insights

Overall, the quantitative findings demonstrate significant performance improvements linked to XAI, while the qualitative insights explain the reasons behind these gains: the establishment of trust and engagement through transparency, along with culturally responsive explanations, enhanced understanding. This alignment provides compelling evidence that XAI can function as both a cognitive tool and a means of promoting equity in under-resourced educational settings. The quantitative results highlight noteworthy performance enhancements attributed to XAI.

Discussion

The findings of this study provide strong evidence that integrating XAI into adaptive learning environments not only enhances academic performance but also improves learners' trust, engagement, and perceptions of fairness. Quantitative analyses showed that students using the XAI-enhanced system significantly outperformed those in the control group, with medium effect sizes indicating that explainability was a meaningful driver of learning gains. The repeated measures ANOVA further confirmed that the XAI group's progress over time was more substantial, highlighting the dynamic role of explainability in sustaining growth across the learning period.

These statistical improvements are best understood in light of the qualitative findings. Students consistently emphasized that explanations transformed their experience of adaptive learning from opaque to transparent. By clarifying why certain content was recommended, the XAI system reduced confusion, increased perceived fairness, and promoted metacognitive reflection. This aligns with earlier work suggesting that transparency mitigates perceptions of algorithmic arbitrariness and fosters learner agency (Shin, 2020; Miller, 2019). The trust-building role of explanations was particularly evident in under-resourced environments, where baseline skepticism of digital technologies is often high (Luckin et al., 2023).

Equally important, the co-design of explanations with teachers ensured that the system was culturally and pedagogically relevant. Teachers noted that when explanations incorporated local contexts such as market transactions or familiar scenarios, students were more motivated and better able to connect abstract concepts with lived experiences. This observation reinforces calls for participatory design approaches in AI for education (Holstein et al., 2020; Khosravi et al., 2022) and highlights inclusivity as not merely a technical but a pedagogical imperative. By embedding cultural resonance, XAI acted as a bridge across linguistic and socio-economic divides, offering a concrete pathway for equity in digital education.

These findings emphasize the dual role of XAI in education. Cognitively, it reduces mental effort and enhances metacognitive engagement. Socially, it fosters epistemic justice by giving learners insight into the mechanisms that shape their educational journeys. This duality suggests that explainability is not merely an added feature but a fundamental requirement for fair and adaptable learning environments. The results provide empirical support for the idea that transparency improves both engagement and fairness (Shute & Rahimi, 2021; Contrino et al., 2024). Additionally, these findings extend our understanding by demonstrating these effects in an African, resource-limited context.

Nevertheless, limitations remain. The short intervention period constrains claims about long-term retention of trust and performance gains. Additionally, the study focused primarily on learner-facing features; future research should explore how teachers leverage explainability tools to adapt their instruction and how longitudinal exposure shapes learner autonomy and resilience. Despite these limitations, the convergence of quantitative and qualitative evidence provides compelling support for XAI as a mechanism for both effectiveness and inclusivity in education.

Conclusion

This study demonstrates that integrating explainable artificial intelligence into adaptive learning systems yields clear advantages in under-resourced educational settings. The quantitative results show that students using XAI-enhanced systems achieved significantly higher learning gains than those using traditional adaptive platforms, even after controlling for baseline knowledge. The qualitative findings clarify why these gains occurred: explanations increased transparency, reduced uncertainty, and created conditions for trust and sustained engagement. When explanations were culturally grounded and pedagogically meaningful, they also strengthened learners' ability to connect new content with familiar contexts.

The results reinforce the argument that the value of XAI in education extends beyond technical interpretability. Explainability functioned as both a cognitive support reducing confusion and encouraging meta cognition and a social mechanism for fairness, inclusion, and epistemic justice. In resource-limited environments where digital skepticism and inequities are common, this dual role becomes particularly important. Although the relatively short intervention limits claim about long-term impact, the convergence of evidence across methods provides a credible basis for asserting that explainability is not optional but essential if AI-driven learning tools are to support equity rather than deepen existing divides.

Recommendations

Based on the findings of this study, it is recommended that explainability be treated as a core requirement in the design and deployment of adaptive learning technologies, particularly in under-resourced educational environments. Educational technology developers and policymakers should integrate learner-facing explanations that are culturally relevant and pedagogically appropriate, ideally through co-design processes that involve teachers and students. Teacher capacity-building is also essential, as educators need to understand and meaningfully incorporate XAI outputs into their instructional decisions. Future research should extend the intervention period to examine the long-term sustainability of trust, performance gains, and learner autonomy, while policymakers should develop clear guidelines that promote transparency, algorithmic accountability, and fairness in AI-enabled learning systems. Finally, further work is needed to explore how teacher-facing explainability tools can enhance instructional planning and strengthen equitable learning opportunities.

References

Altukhi, Z., & Pradhan, S. (2025). Systematic literature review: Explainable AI definitions and challenges in education. arXiv preprint arXiv: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. IEEE Transactions on Learning Technologies.

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. 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: A review. Computers, 11(10), 139.

Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education.

Holstein, K., Wortman Vaughan, J., Daumé, H. III, Dudik, M., & Wallach, H. (2020a). Improving fairness in machine learning systems. Proceedings of the ACM on HCI, 4(CSCW2), 1– 26.

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

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

Hu, Q., & Wang, Y. (2024). Enhancing personalized learning with FOKE. British Journal of Educational Technology, 55(2), 502–519.

Kabudi, T., Pappas, I., & Olsen, D. (2021). AI-enabled adaptive learning systems. Computers & Education, 165, 104143.

Khosravi, H., Kitto, K., & Wong, S. (2022a). Explainable recommender systems in education. Computers & Education: Artificial Intelligence, 3, 100080.

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

Luckin, R., Holmes, W., & Griffiths, M. (2023a). Human-centered AI for education. Nature Machine Intelligence, 5(1), 10–21.

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

Makinde, M. A. (2025). Makes case for investment in AI.

Miller, T. (2019). Explanation in AI. Artificial Intelligence, 267, 1–38.

Muralidharan, K., Singh, A., & Ganimian, A. J. (2019). Technology-aided instruction. American Economic Review, 109(4), 1426–1460.

Ooge, J., Dereu, L., & Verbert, K. (2023). Steering recommendations. arXiv:2303.00098.

Pachler, N., et al. (2023). Explicable AI in education. Learning, Media and Technology, 48(2), 123–138.

Papamitsiou, Z., & Economides, A. (2014). Learning analytics in practice. Educational Technology & Society, 17(4), 49–64.

Petch, J., Di Paolo, A., & Valentine, A. (2022). Opening the black box. Information Systems Frontiers, 24(6), 1687–1719.

Poursabzi-Sangdeh, F., et al. (2018). Manipulating interpretability. arXiv:1802.07810.

Shin, D. (2020a). User perceptions of transparency. Computers in Human Behavior, 108, 106305.

Shin, D. (2020b). Effects of explainability. Computers in Human Behavior, 107, 106569.

Shute, V. J., & Rahimi, S. (2021). Formative feedback and XAI. Computers & Education, 172, 104270.

Wang, Q., Xu, C., & Liu, S. (2024). AI-enabled adaptive learning systems. Interactive Learning Environments.

Wang, Y., Chen, N., & Khan, M. (2022). Visualization and feedback. Interactive Learning Environments, 30(5), 954–967.

Zhao, J., Zhang, W., & He, X. (2021a). XAI and engagement. Educational Technology & Society, 24(3), 52–67.

Zhao, J., Zhang, W., & He, X. (2021b). XAI in adaptive learning. Educational Technology & Society, 24(3), 52–67.