# Explainable and Fair AI Models for Culturally Sensitive Healthcare in Rural Nigeria

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## ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) can revolutionise healthcare in rural and underserved regions by improving accessibility, personalisation, and patient outcomes. However, in Nigeria, infrastructural challenges, cultural sensitivities, low literacy rates, and ethical concerns like algorithmic bias and data privacy hinder their effectiveness. Current AI models, designed for urban contexts, often fail in rural settings due to a lack of contextualised data, leading to inequitable outcomes.

Our research develops an explainable and fair AI framework tailored to Nigeria's rural healthcare systems. By integrating cultural sensitivity, bias mitigation, and rigorous validation techniques, the framework ensures AI tools are trusted, equitable, and effective for marginalised communities. This scalable solution has the potential to advance fairness and transparency in AI while tackling the unique challenges of rural healthcare in low-resource settings.

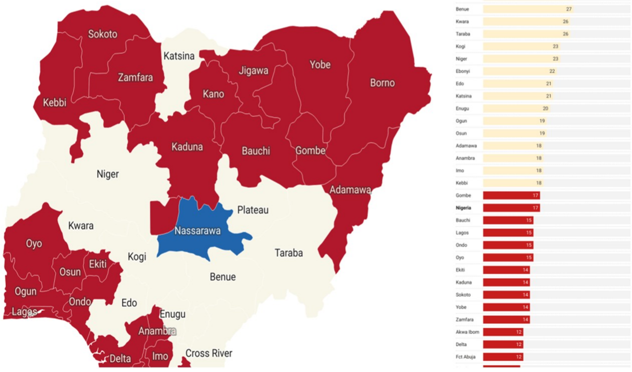


**Fig 1:** Analysis of the distribution of hospitals and population projections across Nigeria

## METHODOLOGY

Using a mixed-methods approach, we collected data through interviews, focus groups, and quantitative techniques, applied bias mitigation (re-sampling, Adversarial Debiasing), ensured explainability with SHAP, validated results with benchmark datasets, and incorporated insights from local stakeholders and global datasets to refine tools like an accessible AI chatbot. We reviewed 70 academic papers, 50 healthcare AI use cases globally, and localised studies. Our approach builds on international lessons while addressing specific Nigerian challenges.

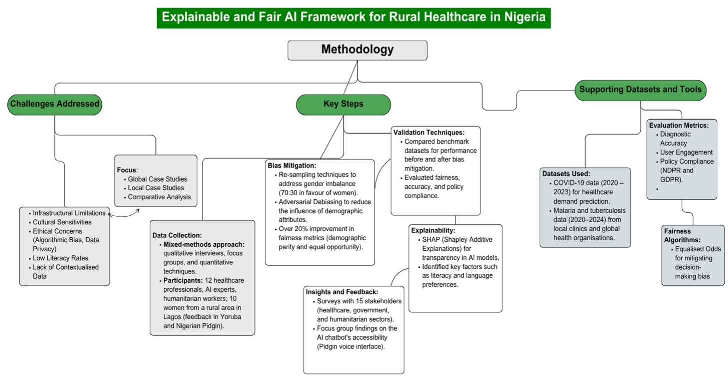


**Fig 1:** Analysis of the distribution of hospitals and population projections across Nigeria

## CONCLUSION AND RECOMMENDATION

This study presents a scalable, explainable, and fair AI framework tailored to Nigeria's rural healthcare systems. By integrating cultural sensitivity, bias mitigation, and localised validation techniques, the framework addresses critical challenges in trust, fairness, and ethics for AI healthcare tools. Synthesising insights from local stakeholders and global frameworks ensures its relevance to low-resource settings. The SHAP-based framework enhances user trust and engagement, particularly among low-literacy populations, by leveraging local languages and addressing gender imbalances in data. Future research should refine these models and expand their applications to areas such as epidemic forecasting and AI-driven diagnostics. Continuous ethical evaluation will be essential to maintain equity, transparency, and trust in AI-powered rural healthcare systems.

## RESULT

The research reveals several critical findings derived from surveys, focus groups, and case studies, including unique adaptations for Nigeria grounded in international frameworks. Notably, 70% of use cases and 65% of the literature emphasise the absence of specific AI governance in rural healthcare, underscoring the urgent need for dedicated regulations. Ethical concerns such as data privacy and cultural insensitivity were identified in 80% of use cases and 75% of the literature, stressing the importance of incorporating these risks into policy frameworks.

Stakeholder engagement, particularly involving local leaders and inclusive gender consultations, was successful in 90% of case studies. This aligns with 60% of the literature, which highlights its significance. Security and risk management, especially concerning misinformation in conflict-prone regions, were flagged in 50% of case studies and 45% of the literature, supporting the call for tailored security measures. Furthermore, the research underscores the importance of synthesising local and global insights, with 85% of use cases and 70% of the literature highlighting international collaboration as a key factor in aligning AI deployments with global standards while addressing Nigeria's specific needs.

| Aspect | International Literature and Use Cases | Local Studies and Use Cases (Nigeria) |
|---|---|---|
| Data Sources | - COVID-19 data from WHO (2020–2023) for healthcare demand prediction. | - COVID-19 data from Nigeria's Ministry of Health for rural healthcare optimisation. |
| | - Malaria prediction models in Kenya using environmental and clinical data. | - Malaria and tuberculosis datasets from Nigerian clinics and global health agencies. |
| Bias Mitigation Techniques | - Adversarial Debiasing and Equalised Odds applied in US healthcare AI systems to ensure fairness. | - Re-sampling techniques and SHAP analysis to correct gender imbalance in Nigerian datasets. |
| AI Chatbot Use Cases | - Chatbot models deployed in India for diabetic retinopathy screening with a focus on accessibility. | - AI chatbot tested with 10 women in Ifako Ijaiye, integrating Pidgin and Yoruba languages. |
| Challenges Highlighted | - Failure of urban-designed AI systems to predict malaria outbreaks in rural Kenya. | - Low literacy levels, cultural diversity, and limited internet access in Nigerian communities. |
| Evaluation Metrics | - Diagnostic accuracy validated against datasets from urban hospitals in Europe. | - Diagnostic accuracy benchmarked against local healthcare workers in rural Nigeria. |
| User Engagement Techniques | - Simplified interfaces in local languages for underserved communities in India and Kenya. | - Voice-based chatbot in Pidgin, increasing accessibility for non-literate users. |

**Fig 3: A side-by-side comparison to illustrates the synthesis of global insights and local applications.**

In terms of AI fairness, over 19% improvement in fairness metrics was achieved after applying re-sampling techniques to address gender imbalances, with pre- and post-resampling comparisons showing no loss in accuracy. Additionally, the use of Adversarial Debiasing successfully reduced demographic biases in model training. SHAP analysis revealed that simplified, localised AI interfaces significantly improved user trust, with local languages such as Nigerian Pidgin contributing to better engagement, particularly for low-literacy populations.

By using SHAP, transparency in AI models is enhanced, as stakeholders can better understand the factors influencing model decisions. This is crucial for building trust, particularly in rural healthcare settings where users may be unfamiliar with AI technologies. The inclusion of fairness algorithms ensures equitable outcomes across diverse populations, addressing bias and promoting fairness in healthcare delivery

1. Key Metrics:

| Metric | Pre-Intervention (%) | Post-Intervention (%) |
|---|---|---|
| Diagnostic Accuracy | 72 | 88 |
| User Engagement | 60 | 85 |
| Policy Compliance | 70 | 90 |

**Fig 4: Impact of AI and Fairness Algorithms on Healthcare Outcomes**

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