



<AI & Equality> African Toolbox | Case study

AI-Powered Malaria Diagnostics: Makerere AI Health Lab Initiative

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This case study is part of the **African <AI & Equality> Toolbox**, which builds upon the methodology of the global <AI & Equality> Human Rights Toolbox—an initiative of Women At The Table in collaboration with the United Nations Office of the High Commissioner for Human Rights (OHCHR). The African Toolbox is a collaboration between the <AI & Equality> initiative and the African Centre for Technology Studies (ACTS). To learn more visit aiequalitytoolbox.com



The challenge: Bridging the diagnostic gap

Malaria remains a critical health challenge in sub-Saharan Africa, where traditional diagnostic methods face significant barriers. The gold standard for malaria diagnosis—microscopic examination of blood smears—requires trained technicians and well-equipped laboratories, resources that are often scarce in the regions where malaria hits hardest.

The Makerere AI Health Lab, led by Dr. Rose Nakasi, confronted this reality directly. In many rural areas across Uganda, the shortage of skilled technicians meant that communities faced delays in diagnosis, subjective interpretations prone to human error, and limited accessibility to diagnostic services. Time constraints in overburdened facilities further compromised patient outcomes.

Rather than accepting these limitations as inevitable, the team recognized an opportunity to leverage AI technology to democratize access to accurate malaria diagnosis—but only if developed with careful attention to the communities it would serve.

A community-centered approach to technical innovation

Defining the Real Problem

The Makerere initiative began with a crucial insight: the challenge wasn't simply technical—it was about health equity and access. The team's objective extended beyond "developing AI for malaria diagnosis" to specifically addressing the unique constraints of resource-limited rural areas in Uganda. This community-driven approach shaped every subsequent decision.

The team composition reflected this understanding from the outset. Rather than working in isolation, they assembled a multidisciplinary group that included not just AI experts and researchers, but local medical practitioners deeply familiar with the context. Local health facilities became integral partners in defining needs and shaping solutions, not merely end users of a predetermined technology.

The technical innovation: Making AI accessible

The centerpiece of the solution—a 3D-printed smartphone adapter that connects to standard microscope eyepieces—exemplifies how technical design can embody values of accessibility and sustainability. This innovation addressed the lack of expensive, dedicated imaging equipment in resource-limited settings by transforming existing microscopes into digital imaging devices.



The choice of smartphone technology wasn't arbitrary—it leveraged devices already present in many communities while ensuring that the diagnostic capability could remain local and sustainable. The 3D-printed adapter could be manufactured locally, reducing dependence on international supply chains and enabling communities to maintain and replace equipment independently.

Confronting data challenges with ethical rigor

Building a Representative Dataset

One of the most significant challenges faced by the team was the scarcity of suitable datasets. Existing datasets were either unavailable or inadequately represented the local context and populations the system was designed to serve.

Rather than compromising on data quality or appropriating inappropriate datasets, the team initiated their own comprehensive data collection effort. This process required navigating complex ethical and bureaucratic landscapes:

- **Ethical Foundations:** The team obtained necessary ethical approvals from relevant authorities, ensuring compliance with research standards and protection of patient rights from the project's inception.
- **Partnership-Based Collection:** They established collaborative relationships with local health facilities, creating partnerships rather than extractive relationships for data collection.
- **Privacy Protection:** Strict data anonymization protocols were implemented to protect patient privacy while still enabling the medical insights necessary for effective AI development.
- **Persistence Through Bureaucracy:** The team acknowledged that “bureaucracies and unclear data policies often slow down progress,” but demonstrated commitment to working within these systems while advocating for clearer, more enabling policies.

The Human Rights Impact Assessment Integration

The data collection process exemplified key principles from human rights impact assessments. The team ensured that data subjects provided informed consent, that privacy was rigorously protected, and that the sensitive nature of health information was respected throughout the process.

Their approach treated community data as an asset to be protected and shared responsibly, rather than a resource to be extracted. This philosophy shaped not only how data was collected, but how insights would be shared back with communities and how the technology would be deployed.



Technical excellence serving health equity

Model Development with Purpose

The AI model development process balanced technical sophistication with practical constraints and community needs. Key decisions reflected the team's commitment to creating tools that would genuinely serve health equity:

- **Accuracy and Speed:** The system achieved 99% accuracy in detecting malaria parasites alone, with remarkably efficient inference time of 5 seconds. This speed was crucial for practical deployment in busy clinical settings where patients cannot wait extended periods for diagnosis.
- **Transparency About Limitations:** When the system's accuracy dropped to 74% for multi-class detection including white blood cells, the team transparently acknowledged this limitation and committed to ongoing efforts to address the issue. This honesty about performance trade-offs demonstrates commitment to responsible AI development.
- **Accessibility-First Design:** The smartphone-based interface prioritized usability in resource-constrained environments, ensuring that the tool could function effectively even with limited technical infrastructure.

Addressing Algorithmic Bias

The team's attention to performance discrepancies across different detection tasks highlighted their awareness of potential bias issues. Their commitment to "ongoing efforts to address this issue" demonstrated understanding that algorithmic fairness requires continuous attention and refinement, not just initial consideration.

Real-world validation and community engagement

Testing in Authentic Contexts

The validation process emphasized real-world performance over laboratory-controlled conditions. Field testing was conducted in actual healthcare settings where the system would ultimately be deployed, directly exposing and addressing practical challenges that wouldn't emerge in controlled environments.

The team actively collected feedback from healthcare workers to ensure user-friendliness and practical application. This participatory approach ensured that the tool would meet the actual needs of its intended users rather than theoretical requirements defined by developers.



Rigorous Comparison: The AI system's diagnoses were compared with those of experienced technicians, providing robust validation of accuracy in real-world conditions while respecting the expertise of human practitioners.

Addressing the Human-AI Partnership

Throughout the development process, the team emphasized that AI serves as a support tool rather than a replacement for human expertise. This philosophy addressed concerns about job displacement while positioning AI as a means of enhancing human capabilities and extending expert-level diagnosis to underserved areas.

The approach recognized that healthcare workers bring irreplaceable knowledge, cultural understanding, and patient relationships that AI cannot replicate. The technology was designed to complement and enhance these human capabilities rather than substitute for them.

Impact and sustainable development

Immediate Outcomes

The project demonstrated measurable potential for improving healthcare delivery in resource-limited settings:

- **Diagnostic Accuracy:** Potential reduction of diagnostic errors and subjective interpretation
- **Accessibility:** Increased access to quality diagnostics in remote and under-resourced regions
- **Efficiency:** Faster diagnostic turnaround times enabling more timely treatment
- **Capacity Building:** Decision support tools that enhance rather than replace healthcare worker capabilities

Long-Term Vision

The Makerere Health Lab's plans for expansion reveal a comprehensive vision for technology-enabled health equity. Future directions include:

- **Disease Coverage Expansion:** Adapting the AI diagnostics approach to other diseases such as cervical cancer and tuberculosis, addressing multiple health challenges with similar community-centered methodology.
- **Telehealth Integration:** Exploring telehealth platforms for remote expert consultations, extending specialist knowledge to underserved areas while maintaining community ownership of diagnostic capabilities.
- **Cultural Accessibility:** Adapting tools for local languages, ensuring that linguistic barriers don't prevent communities from benefiting from diagnostic advances.



Lessons for Human Rights–Based AI Development

Key Principles Demonstrated

The Makerere initiative offers several crucial insights for AI development that promotes rather than undermines human rights:

- **Community Partnership from Inception:** The most sophisticated AI system fails if communities don't trust it, understand it, or have agency in its deployment. Starting with community needs rather than technical capabilities ensures that AI serves justice rather than perpetuating existing inequities.
- **Ethical Rigor Throughout:** Privacy protection, informed consent, and transparency aren't add-ons to technical development—they're foundational requirements that shape every aspect of system design and deployment.
- **Technical Choices Reflect Values:** Every decision—from smartphone compatibility to local manufacturing capability—embodies assumptions about users and priorities. Designing for African contexts required fundamental rethinking of standard approaches.
- **Sustainability Through Local Ownership:** Long-term success depends on communities having genuine ownership and control over the technology, not just access to it.



Mapping the AI Lifecycle HRIA Framework for the Makekere Health Lab case

1 Stage 1: Objective and Team Composition

- **Purpose & Context:** The team explicitly addressed malaria's disproportionate impact on resource-limited rural areas in Uganda, recognizing healthcare access as a justice issue rather than merely a technical challenge.
- **Community Engagement:** Local health facilities were integrated as partners from the beginning, not just end users. The team included local medical practitioners deeply familiar with the context, ensuring lived experience informed the development process.
- **Team Composition:** The multidisciplinary team combined AI experts, researchers, and crucially, local medical practitioners who understood the real-world constraints and cultural context of deployment.
- **Effects Assessment:** The objective was framed around democratizing access to expert-level diagnosis, explicitly targeting communities historically excluded from quality healthcare due to geographic and economic barriers.

2 Stage 2: Defining System Requirements

- **Technical Requirements Driven by Community Needs:** The choice of smartphone-based technology and 3D-printed adapters directly addressed the resource constraints identified by local partners. Requirements prioritized accessibility and local sustainability over technical sophistication.
- **Ecosystem of Values:** The team balanced multiple values - diagnostic accuracy (99% for parasite detection), speed (5 seconds inference time), accessibility (smartphone compatibility), and sustainability (locally manufacturable components).
- **Explainability:** The system was designed to provide decision support for healthcare workers rather than replace human judgment, maintaining transparency about AI capabilities and limitations.
- **Privacy Considerations:** Requirements included strict data anonymization protocols and local processing capabilities to protect patient privacy from the design stage.



3 Stage 3: Data Discovery

- **Ethical Data Collection:** When suitable datasets were unavailable, the team proactively created their own dataset through ethical protocols including institutional review board approvals and strict anonymization procedures.
- **Community Partnership:** Data collection involved collaborative relationships with local health facilities as partners rather than extractive relationships. The approach treated community data as an asset to be protected and shared responsibly.
- **Addressing Data Bias:** The team recognized that existing datasets didn't adequately represent local populations and contexts, leading to their decision to create representative datasets specifically for their target communities.
- **Transparency:** The team openly acknowledged bureaucratic challenges in data access while maintaining commitment to ethical standards, demonstrating transparency about process constraints.

4 Stage 4: Selecting and Developing a Model

- **Model Selection for Context:** Technical choices prioritized practical deployment in resource-constrained environments. The smartphone-based interface was chosen specifically for its accessibility and sustainability in the target context.
- **Fairness Considerations:** The team transparently acknowledged performance differences between single-class (99% accuracy) and multi-class detection (74% accuracy), committing to ongoing efforts to address these disparities.
- **Explainability Requirements:** The model was designed as a support tool that enhances rather than replaces human expertise, maintaining appropriate human oversight and decision-making authority.
- **Environmental Considerations:** The choice of smartphone technology and local manufacturing capability reduced environmental impact compared to importing expensive diagnostic equipment.

5 Stage 5: Testing and Interpreting Outcome

- **Real-World Testing:** Field testing was conducted in actual healthcare settings where the system would be deployed, ensuring validation under authentic conditions rather than controlled laboratory environments.
- **User Feedback Integration:** The team actively collected feedback from healthcare workers to ensure user-friendliness and practical application, making the end users central to the validation process.
- **Performance Validation:** AI diagnoses were rigorously compared with experienced technicians, providing robust validation while respecting existing human expertise.
- **Operation Manual Development:** The focus on user-centric design and practical application suggests development of accessible training and operation procedures, though specific details aren't provided in the source material.



6 Stage 6: Deployment & Post-Deployment Monitoring

- **Sustainable Deployment Strategy:** The 3D-printed adapter design enables local manufacturing and maintenance, ensuring communities can sustain the technology independently rather than depending on external support.
- **Continuous Adaptation:** Plans for expansion to other diseases (cervical cancer, tuberculosis) and telehealth platforms demonstrate commitment to ongoing adaptation based on evolving community needs.
- **Cultural Accessibility:** Future plans include adapting tools for local languages, showing understanding that deployment must address linguistic and cultural barriers.
- **Monitoring Through Expansion:** The systematic approach to expanding the framework to other health challenges suggests built-in monitoring and learning processes, though specific monitoring mechanisms aren't detailed in the source material.
- **Community Agency:** The emphasis on decision support rather than replacement tools suggests deployment strategies that maintain community control and professional agency in health decision-making.

Key Insights from the Lifecycle Mapping

The Makerere case study demonstrates several critical insights for human rights-based AI development:

- **Integration Throughout:** Human rights considerations weren't added as an afterthought but shaped every stage from initial problem definition through ongoing expansion plans.
- **Community Partnership:** Genuine community engagement occurred at each stage, with local partners having real influence on technical decisions rather than token consultation.
- **Ethical Foundations:** Privacy protection, informed consent, and transparency were foundational requirements that shaped technical architecture and deployment strategies.
- **Sustainability Focus:** Each stage prioritized long-term community ownership and control over short-term technical optimization or external dependency.
- **Continuous Learning:** The commitment to expansion and adaptation demonstrates understanding that human rights-based AI development is an ongoing process of learning and refinement rather than a one-time project.



Conclusion:

Technology in Service of Health Justice

The Makerere AI Health Lab's AI-powered malaria diagnostics initiative demonstrates that technology can serve human rights and health equity when developed with genuine community participation throughout the lifecycle. Rather than imposing external solutions, the project created tools that emerge from and serve community-identified needs.

The technical innovations—from 3D-printed adapters to smartphone-based AI—represent more than engineering achievements. They embody a philosophy that technology should democratize rather than concentrate capabilities, empower rather than replace human expertise, and serve justice rather than perpetuate existing inequities.

Most importantly, the project's commitment to ongoing expansion and adaptation demonstrates understanding that AI development for health equity is not a one-time intervention but an ongoing partnership with communities. This approach offers a model for how AI can genuinely serve the right to health, creating technology that enhances human dignity rather than undermining it.

The lessons from Makerere extend far beyond malaria diagnosis, providing a framework for any AI development that seeks to serve rather than exploit the communities it touches. In an era where AI often concentrates power and resources, this initiative demonstrates an alternative path—one where technology becomes a tool for justice, equity, and human flourishing.

About the case study and author

This case study analyzes research conducted by Makerere University, examining smartphone-based digital Microscopy Images for malaria diagnosis using Artificial Intelligence across Health facilities in Uganda between 2016 - 2024.

Dr Rose Nakasi leads the Makerere Health Intelligence lab that is specializing in advancing Artificial Intelligence and Data Science for developing automated tools and techniques for improved health especially in low resourced settings. She is a Principal investigator for the DS-I Malaria project under the DS-I Africa consortium funded by the NIH to support effective malaria diagnosis and surveillance in Uganda.

Other contributors to this case study are Caitlin Kraft-Buchman, Emma Kallina, and Sofia Kypraiou, authors of the original *Framework to AI Development: Integrating Human Rights Considerations Along the AI Lifecycle* upon which the Toolbox structure is based. Additional contributors are Amina Soulimani and Pilar Grant, from Women at the Table and the <AI & Equality> Human Rights Initiative.