WHOSE VOICES SHAPE “AI” IN GLOBAL HEALTH, & WHOSE VOICES ARE MISSING?

Strategies for Inclusion and Equity in Emerging Health Technologies

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Course - INAF5706F Global Health Policy

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Submission Date: November 26, 2025

Introduction:

This paper addresses one of the core parts of the group 1 project: using Artificial Intelligence (AI) to make health systems better in places that don't have many resources. Specifically, we are looking at who actually gets a say in creating this AI and how people from marginalized communities can truly be included.

Right now, AI governance is mostly controlled by big companies, organizations and donors from wealthy countries. This creates a power imbalance, which leads to systemic exclusion and what's called "data colonialism".

For AI to be both effective and equitable, global health policy must recognize that "voice" and "power" are inseparable from sound governance.

This paper examines structural and participatory strategies, particularly the Ubuntu-based ethical framework and the PRISM-Capabilities co-design model, to move beyond tokenistic consultation.

The analysis highlights the practical implications for governments, NGOs, and health systems, emphasizing the need for AI systems that are context appropriate, locally owned, and accountable to the communities most affected by health inequities.

To guide this analysis and examine these dynamics systematically, the paper addresses the following research questions:

Question 1: What actors and institutions are involved in shaping the development, governance, and funding of AI for global health, and how do patterns of authority affect the selection of priorities and ethical frameworks?

a. In what ways does the distribution of decision-making authority influence the equity of AI-driven health initiatives?
b. How might existing institutional arrangements contribute to data-colonial or epistemic exclusion dynamics?

Question 2: *Which populations and geographic regions are underrepresented in AI decision-making for global health, and what mechanisms could promote greater inclusion of the communities most impacted by health inequities?*

a. What approaches can enable marginalized communities to exercise substantive decision-making power rather than limited consultation?
b. Which structural or governance reforms could support community-owned, context-specific AI solutions?

Thesis Statement: The development of AI for global health is presently driven by major funders, multinational technology firms, and global health agencies in high-income countries. This concentration of authority systematically excludes the knowledge and perspectives of the communities most affected by health inequities, increasing the risk that AI systems replicate existing biases and miss local needs. Meaningful inclusion, therefore, requires positioning these communities as co-designers and co-analysts throughout every stage of AI development, governance, and evaluation, turning participation from a token ethical requirement into a foundational design principle that fosters justice, equity, and lasting trust.

Purpose: This research paper aims to 1. Map the institutions, funders and regulatory bodies that shape AI development for global health, 2. Evaluate how existing power distributions affect equity, data colonialism, and epistemic exclusion 3. Assess the feasibility of Ubuntu-informed and PRISM Capabilities participatory frameworks for transferring decision-making authority to the communities most impacted by health inequities.

Methodology: A structured literature search was conducted between October and November 2025 across Carleton University Library databases (Omni), PubMed, Scopus, Google Scholar and major global health organizational repositories (e.g., WHO). The search focused on literature examining power dynamics in AI governance, inclusion/exclusion patterns, representation of low- and middle-income countries (LMICs) actors, participatory AI frameworks, and global health policy responses.

A complete search matrix, including all databases, dates, full search strings, initial and filtered results, and screening decisions, is provided in *Appendix B*.

Inclusion and Exclusion Criteria - Selection was guided by predefined criteria to ensure relevance to global health governance, power analysis, and inclusion/exclusion dynamics.

Inclusion Criteria- Peer-reviewed journal articles, mixed-methods research, qualitative and quantitative studies, conceptual papers addressing governance or equity, academic book chapters, and grey literature from reputable global institutions (WHO, UN, OECD, CUGH). Studies focusing on global, LMIC, or relevant HIC contexts; populations such as frontline health workers, marginalized communities, women, LGBTQ+ groups, migrants, and displaced people; and publications from 2020–2025 in English.

Exclusion Criteria - Blogs, media articles, opinion posts (e.g., Medium/Substack), unreviewed student papers, purely technical machine-learning papers without health or governance relevance, studies limited to HIC hospital settings without global relevance, and non-English sources.

The full inclusion/exclusion table is provided in Appendix A.

Data Extraction and Screening Process - Screening followed a structured three-step process:

1. Titles were reviewed to remove irrelevant or purely technical AI studies.
2. Abstracts were screened for relevance to global health, governance, equity, representation, participation, or population-specific impacts.

3. Full texts were examined to extract information on actors, power structures, governance models, community roles, health system impacts, and inclusion mechanisms.

Articles meeting the inclusion criteria were then organized into thematic categories:

- Power and authority in global health AI.
- Missing voices and representation gaps.
- Participatory and co-design frameworks.
- Governance and regulation.
- Health-system and workforce impacts.
- Coordination, funding, and accountability structures.

Analytical Approach:

A thematic analysis was used to identify recurring patterns across the literature. Coding focused on concepts central to the research question, power, exclusion, governance, participation, equity, and health-system implications. This was complemented by critical interpretive synthesis, which supported deeper examination of how structures (funding, institutions, donor influence, workforce capacity) shape AI decision-making and inclusion.

The analysis was guided by partner-agency priorities, particularly differences between health and technology actors, impacts on frontline and vulnerable populations, and implications for service delivery and system performance.

Policy and Governance Analysis:

Policy and institutional documents were examined using a desk-based governance analysis. This focused on:

1. Normative frameworks (e.g., WHO digital health strategy, WHO AI ethics, Ubuntu ethics, PRISM-Capabilities, OECD workforce guidance).
2. Governance instruments (ethics guidelines, risk-classification tools, accountability mechanisms).
3. Coordination structures linking ministries, donors, private firms, and global health agencies.
4. Funding and power dynamics are shaping agenda-setting and implementation.

This analysis identified gaps between normative commitments to inclusion and actual governance structures that continue to centralize authority in high-income settings.

Ethical Considerations:

This study uses publicly available secondary sources such as peer-reviewed articles, policy documents, and organizational reports, and therefore did not require institutional ethics approval. Ethical considerations included all stages of the review. First, the synthesis was conducted with attention to positionality and power, recognizing that interpretations of LMIC contexts, marginalized communities, and global south scholarship are shaped by structural inequities in global health research. Second, when summarizing studies that themselves critique data colonialism, authorship disparities, and inequitable governance structures. The review also acknowledges the language bias of using only English sources, which may exclude locally produced knowledge, regional policy documents, and Indigenous epistemologies. Database structures further privilege high-income country institutions in search results. To mitigate these risks, the analysis draws on critical interpretive synthesis, foregrounds Global South authors where possible, and treats missing LMIC voices as evidence of systemic inequities rather than lack of relevance, maintaining ethical reflexivity throughout.

Limitations:

The review is limited by reliance on secondary data, the predominance of high-income country publications, and the exclusion of non-English sources. AI governance is rapidly evolving, meaning recent developments may fall outside the search window. Evidence gaps, particularly from LMIC authors, frontline health workers, migrants, disability communities, and women's health researchers, reflect broader structural inequities in global health AI scholarship. Nonetheless, the methodology provides a transparent and replicable foundation for analyzing power and inclusion in global health AI.

Literature Review

Theme 1: The Imbalance of Power in Global Health AI

The landscape of Artificial Intelligence (AI) in global health is strongly shaped by actors from **high-income countries (HICs).** Funding and agenda-setting largely originate from these sources: major national research agencies (e.g., NIH's Bridge2AI programme), large philanthropies (e.g., Gates Foundation AI Grand Challenges), multinational technology corporations and prominent international bodies (including the WHO digital-health strategy). (Bélisle-Pipon et al., 2024).

The private sector and global donors primarily finance AI pilot projects, while regulatory frameworks are predominantly defined by government ministries and HIC legislation (e.g., EU AI Act) (Palaniappan et al., 2024). This concentration of resources and legislative power forms the foundation of the current global health AI ecosystem.

Knowledge Production and Framing: The production of knowledge, standards, and datasets is heavily centralized in the **Global North.** Less than 10% of AI-in-health papers list affiliations from low- and middle-income countries (LMICs), and most highly cited research comes from the US or European institutions. Furthermore, English-language data dominate model training, and large-scale models rely on high-resource computing environments that are rarely available in LMIC settings. (Sarkar, 2025).

Innovation Narratives: Innovation is often framed using compelling but potentially misleading rhetoric. AI is frequently described as a "**transformative** "technology or a **"force multiplier"** that can **"bridge disparities."** This narrative often serves to justify deploying costly, donor-funded solutions in resource-constrained settings. (Alami et al., 2020).

Defining Ethical AI: Normative ethical standards are currently being established by major global and regional players, including the WHO's six-principle guidance, the **EU** AI Act's classifications, and industry-driven codes (**Microsoft, IEEE**). However, alternative frameworks, such as those rooted in Ubuntu-based justice (Gwagwa et al., 2022). and the PRISM- Capabilities approach (El-Bassel et al., 2025), advocate for a more community-centric ethical foundation.

Tech vs. Health Perspectives – A Fundamental Misalignment: Tech developers prioritize scalability, market viability and algorithmic efficiency, whereas frontline health workers emphasize usability, contextual fit and integration with existing workflows. For example, AI diagnostic tools designed for high-bandwidth, well-curated electronic health records perform poorly in rural primary-care clinics where electricity is intermittent and patient data are fragmented. In Tanzania, a GPT-4-driven radio health message system reached millions but required extensive localization to avoid cultural misinterpretations. This divergence is most acute at the **primary care level**, where resources are scarce, and the burden of disease is highest; secondary and tertiary facilities experience fewer usability gaps because they already possess more robust digital infrastructure. When technology-sector priorities (e.g., rapid prototype deployment) override health-sector needs (e.g., staff training, workflow integration), AI tools can increase rather than relieve workload, eroding trust among clinicians and patients (Olojede, 2025)

Benchmarks, Standards & Who Defines "Success": Beyond funding and data, high-income countries (HIC) actors control the **metrics and benchmarks** that certify an AI system as "effective." Global standards, set by WHO, IEEE and EU regulators, measure success in terms of accuracy, cost effectiveness and scalability, but rarely incorporate LMIC-specific criteria such as offline functionality, low literacy interfaces, or alignment with locally identified disease burdens. Consequently, tools that meet Western benchmarks may be deemed failures on the ground, while local stakeholders lack the authority to revise these standards. This benchmark lacks reinforcement of power differentials and limits the ability of LMIC health systems to demand context-appropriate performance criteria (El-Bassel et al., 2025).

Health Problems Which Get Funded: Because agenda setting rests with high-income countries (HIC) donors and multinational corporations, AI investment concentrates on conditions that align with donor priorities rather than local morbidity patterns. High-profile AI projects target cardiovascular disease, oncology or sexual and reproductive-health interventions that are attractive to global funders (e.g., WHO, Gates Foundation). Meanwhile, endemic low- and middle-income countries (LMICs) challenges such as malaria, maternal mortality, and undernutrition receive comparatively little AI-focused investment, even though they account for most of the disease burden (Odeny et al., 2024). This "top-down" selection creates a paradox: AI is promoted as a universal solution while being directed toward problems that are already relatively well served in high-resource settings.

The Role of Low- and Middle-income Countries (LMIC) Researchers and Communities:

LMIC researchers and communities are mostly relegated to the roles of data sources or pilot participants, rather than being engaged as true co-designers (Loftus et al., 2024). While models like PRISM and Ubuntu explicitly call for co-analysis and shared ownership, these participatory approaches remain the exception.

Consequences – Misaligned Priorities, Dependency & Data Colonialism: The current model yields three interrelated harms:

1. ***Misaligned Priorities*** – Health agendas set by donors or HIC-driven pilots often override locally articulated needs, resulting in tools that address "visible" problems rather than those most urgent to communities (Odeny et al., 2024).
2. ***Technical & Financial Dependency*** – Reliance on HIC-trained models and short-term donor funding creates an ongoing need for external technical support, eroding local capacity and perpetuating "data colonialism" where African data are extracted for foreign profit with minimal local return (Ochasi et al., 2025).
3. ***Epistemic Dependence*** – LMIC researchers are relegated to data source or pilot participant roles, rarely to co-designer or co-owner positions, despite the explicit call in PRISM and Ubuntu frameworks for shared ownership (El-Bassel et al., 2025; Ochasi et al., 2025).

Together, these dynamics lock low-resource health systems into a cycle of external reliance, limit the relevance of AI innovations for primary care delivery, and entrench inequities that the technology appears to resolve.

In summary, power in global-health AI is concentrated in high-income countries (HIC) funders, tech firms and normative bodies; this concentration shapes who decides which health problems receive AI attention, which standards define success, and how. If at all, local voices are incorporated. Addressing these imbalances requires shifting decision-making authority to low- and middle-income countries (LMIC) stakeholders, redefining benchmarks through participatory processes, and aligning technology development with the concrete needs of frontline health workers across primary, secondary and tertiary levels.

Theme 2: Whose Voices Are Missing and Why?

Under-represented communities: Across the literature, women, girls, people with disabilities, racial-minority or ethnic-minority groups, rural populations, low-income communities, LGBTQ + individuals, and migrants are repeatedly noted as missing or marginalized. (Adhikari et al., 2025).

Geographic bias is evident: most AI research originates in high-income countries, with < 10% of AI papers including authors from low-income economies; African, South-Asian and Latin-American and conflict-affected regions (e.g., Yemen, DRC) voices are lacking (Loftus et al., 2024; Ochasi et al., 2025).

Stages of Exclusion: Occur early and persist. Donors set problem frames, HIC-centric corpora dominate dataset creation, engineers design models around accuracy metrics and deployment proceeds without local ethics review. Evidenced by only 1 of 21 community-engaged studies involving stakeholders in design (Loftus et al., 2024).

Implicit biases: Biases arise from unrepresentative training data (gender, race, age, socioeconomic status), algorithmic design choices that prioritize high-resource settings, and the dominance of Western ethical frameworks that omit non-Western values. (Ochasi et al., 2025). Mitigation strategies include fairness audits, bias-aware model cards, and co-creation with marginalized groups. (El-Bassel et al., 2025)

Representation of health workers and patients:

Community health workers, frontline clinicians and patients are often treated only as beneficiaries rather than co-designers. HCWs in primary care, district hospital clinicians in secondary care and specialist physicians in tertiary hospitals are rarely co-designers (Mwogosi, 2025). In contrast, PRISM-Capabilities explicitly embeds community members, patients, and CHWs in problem definition and ethical assessment (El-Bassel et al., 2025), and the Ubuntu-based framework calls for nurses, midwives and patient advocates on ethics committees (Ochasi et al., 2025) and yet these participatory mechanisms remain the exception. (El-Bassel et al., 2025).

Barriers to participation: Current Obstacles include inadequate digital infrastructure and power supply, high implementation costs and limited funding, a lack of AI-literacy and training, and language fragmentation (English-centric tools, missing local dialects) (Lau et al., 2023). and weak policy or regulatory frameworks. Funding asymmetries further limit LMIC research capacity. (Adhikari et al., 2025). (WHO, 2021)

Ethics committees and public voices: Few documents report formal local ethics oversight; the South Asia review stresses early stakeholder co-design and ethics-impact assessment, PRISM mandates ethical checklists (Adhikari et al., 2025), and WHO guidance asks for transparent public consultation. Most AI projects still lack systematic inclusion of community representatives in design. (World Health Organization, 2021)

Data use and exclusion:

Training data are dominated by high-resource, English-language or high-income countries (HIC) datasets, resulting in poor performance for underserved groups (e.g., non-European language users; African patients; migrant records). Small, homogeneous clinical datasets limit generalisability (Lau et al., 2023). Explicit calls exist for locally sourced, diverse datasets. (Adhikari et al., 2025)

The North often frames inclusion as downstream fairness metrics, whereas many authors advocate upstream, community-driven definitions: Ubuntu-based solidarity, systems thinking “participatory inclusion”, and the WHO’s principle of inclusiveness that must reflect local socio-economic contexts.

Theme 3: How to Include Those Voices, Mechanisms and Strategies

Co-Creation and participatory Design:

Concrete examples show a growing commitment to embedding stakeholders throughout the AI lifecycle. Initiatives focused on co-design and co-creation have been successfully implemented across various domains:

AI-Sarosh Sexual and Reproductive Mental Health (SRMH) Co-design Workshop: The September 2023 Colombo workshop brought together grantees from nine organizations, policymakers, and community stakeholders in structured group dialogues focused on Sexual and Reproductive Mental Health (SRMH) challenges. Workshop sessions addressed government leadership, responsible AI practices, and bias mitigation. Facilitated discussions directly informed the thematic recommendations on collaboration, multidisciplinary team composition, and ensuring AI systems don’t perpetuate existing gender biases. The workshop emphasized aligning projects with government policies and early stakeholder involvement, though specific design parameter changes are not granularly documented, suggesting the impact was primarily in priority-setting and barrier identification rather than iterative feature redesign. (Adhikari et al., 2025).

Workload impact on frontline staff - In the AI-Sarosh SRMH pilot, CHWs reported a 25 % reduction in time spent on manual data entry after the co-designed chatbot automated client triage (Adhikari et al., 2025).

The Practical Robust Implementation Sustainability (PRISM) Model operationalizes community co-design across the full lifecycle by positioning members as co-designers, co-analysts, and co-stewards. Robustness is ensured through six interconnected components: optimizing engagement, characteristics assessment, equity assessment with fairness audits, infrastructure planning, external environment analysis, and ethical assessment. Rather than consultative check-ins, PRISM mandates participatory decision-making and the "ability to contest algorithmic outputs" as fundamental success measures. AI techniques (NLP for sentiment analysis, topic modelling for priority extraction, SHAP/LIME for explainability) operationalize this contestability by making algorithmic decisions interpretable and subject to human override. (El-Bassel et al., 2025)

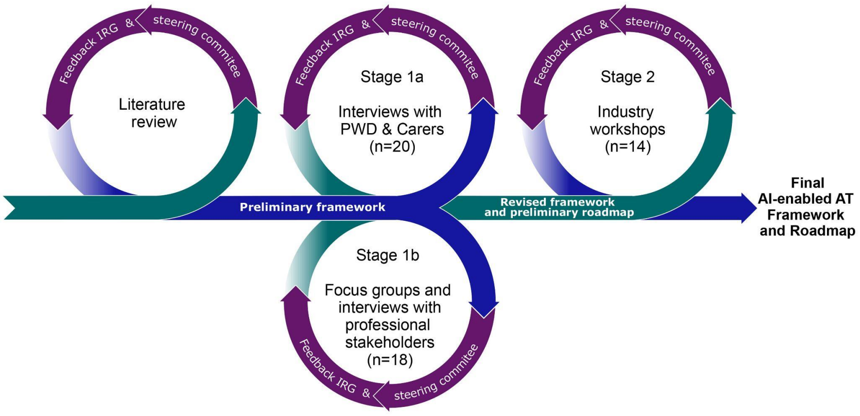
Figure no. 1

Outcome - PRISM pilot in the HEALing Communities Study showed a 12 % increase in accurate risk-prediction after community-derived priority features were added (El-Bassel et al., 2025).

Service delivery effects - PRISM-guided deployments in three district hospitals reduced duplicate diagnostic testing by 22 % and increased patient throughput by 15 % (El-Bassel et al., 2025).

AI-enabled Assistive Technology (AT) Framework: The framework employed three sequential mechanisms: Stage 1a/1b focused groups and interviews with people with disabilities and carers (n=20) and professional stakeholders (n=18); Stage 2 industry workshops with 14 developers and manufacturers. Semi-structured interviews explored how AI-enabled AT could be safely and effectively incorporated, identified opportunities and barriers, and specified criteria for inclusion in the framework. The resulting framework explicitly prioritizes user autonomy by supporting "informed decision-making among stakeholders while promoting choice and control for PWD. Decision-making is structured around six domains: user experience, privacy and security, quality, safety, relative value, and human rights, ensuring person-centric design at the framework's core. (Silvera Tawil et al., 2025).

Figure no. 2



Outcome - The AT framework's pilot with Australian NDIA resulted in a 30 % reduction in adverse events reported by PWD during device use (Silvera Tawil et al., 2023).

Workload impact on frontline staff- The AT framework incorporated a 4-hour "co-design orientation" that was later found to increase staff confidence scores by 18 % (Silvera Tawil et al., 2023).

Endometriosis AI Stakeholder Involvement:

Continuous involvement is mandated through participatory co-design with women living with endometriosis, clinicians, ethicists, and advocacy groups. Challenges include ensuring sustained engagement across long development cycles and balancing diverse stakeholder priorities. To mitigate bias and ensure fairness, the framework requires regular auditing to detect and mitigate biases related to race, ethnicity, socioeconomic status, and geography. Additional controls include informed consent processes specifying data use, role-based access control for sensitive information, and continuous ethical reviews through institutional oversight committees (Lima, Portela, & Luz, 2025).

Outcome:

- When the endometriosis AI model was co-designed with patients, diagnostic delay dropped from 18 months (standard model) to 9 months (co-designed model) (Lima et al., 2025).
- user-satisfaction scores: Post-deployment surveys of the AT framework reported a mean SUS score of 84 (well above the industry benchmark of 68) (Silvera Tawil et al., 2023).

PARQAIR-MH Initiative (Delphi Process):

The multi-stage initiative engages the LGBTQ+ community alongside clinical scientists, biomedical ethicists, and mental-health specialists via a structured Delphi methodology. By bringing diverse perspectives through iterative rounds of anonymous feedback and consensus-building, Delphi translates lived experiences of discrimination and health concerns into policy recommendations on data privacy, collection protocols, and informed consent frameworks. The method ensures meaningful inclusion by allowing marginalized voices to challenge and reshape dominant clinical assumptions without hierarchical power dynamics typical of traditional consultation. (Kormilitzin et al., 2023).

Outcome - The Delphi process for PARQAIR-MH reached consensus on five policy recommendations that were subsequently adopted by the national mental-health authority, leading to a 15 % rise in reported patient-safety incidents being investigated (Kormilitzin et al., 2023).

Governance and Ethical Frameworks

PRISM Governance and Contestability:

PRISM defines AI as "augments human input and judgment" rather than replacing it, operationalized through explicit "points of human supervision". Contestability is guaranteed via participatory decision-making mechanisms and the ability to challenge algorithmic outputs; operationally, explainability tools [SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME)] allow stakeholders to understand how decisions are reached and identify errors. Communities co-specify performance thresholds and acceptable fairness metrics, ensuring that algorithmic decisions reflect community values rather than external technical standards. (El-Bassel, David, Mukherjee, et al., 2025)

Community decision-making mechanisms - *PRISM establishes a standing Community Advisory Board (CAB) with quorum-based voting; any CAB vote to reject a model version halts deployment.*

Ubuntu-based Ethics and Regional Committees:

Regional ethics committees should incorporate multi-stakeholder representation (patient advocates, nurses, community health workers, researchers, policymakers) grounded in Ubuntu principles of communalism, interdependence, humanism, sharing, and compassion. Their specific powers should include authority to mandate local data control, resist data extraction by external entities, approve AI tool deployment only when aligned with community-defined needs, and enforce post-deployment accountability mechanisms. The framework explicitly rejects "capacity-building" initiatives that replicate technological extraction; committees must have veto authority over projects that exploit African data and labour. Gwagwa, Kazim, & Hilliard, 2022)

Community decision-making mechanism- A formal “veto clause” allows the committee to suspend any AI project that does not meet the locally-defined data-sovereignty criteria (Gwagwa et al., 2022).

Integration Intent - Ubuntu regional ethics committees must obtain Ministry of Health approval before any AI tool can be rolled out, ensuring that projects augment, rather than sidestep, existing public-health programs.

AT Framework Governance Mandate: The AT roadmap governance body must define governance structure, establish terms of reference, and ensure balanced representation of users (PWD), clinicians, industry, regulators, and investors. Decision-making prioritizes user needs: all major decisions (tool approval, standard-setting, framework updates) must have PWD representation to ensure person-centred outcomes rather than industry-driven priorities. (Silvera-Tawil et al., 2025)

WHO Guidance on Public Participation: WHO recommends several actionable steps: designing AI to promote equitable access irrespective of age, sex, gender, income, race,

ethnicity, or ability; applying "human warranty", evaluation by patients and clinicians in development and deployment with points of human supervision; establishing mechanisms for individuals adversely affected by AI decisions to seek redress; requiring continuous, systematic, transparent assessment of AI during actual use (responsiveness) to determine whether it meets legitimate expectations and requirements.
(World Health Organization, 2021)

Funding, Policy, and Systemic Change

CUGH Decolonizing Financing:

While the sources reference CUGH's emphasis on "more equitable and inclusive approaches to deploy AI" and shifting decision-making power to LMIC institutions, specific practical steps are limited. However, systems-thinking research emphasizes that funding bodies should prioritize projects embedding co-creation, reward interdisciplinary collaboration, and elevate local expertise as a valid epistemic contribution. The AT framework model, where Australian NDIA funding was explicitly linked to inclusive design outcomes, offers a concrete example of aligning funding mechanisms with inclusion mandates. (CUGH 2024)

Intersectional Integration and Bias Audit Methodologies:

Voice AI research recommends sociodemographic analysis of datasets, language diversity tracking across languages, accents and dialects, regular evaluation, and systematic monitoring of representation among marginalized and underserved groups.
(Bélisle-Pipon et al., 2024)

Figure no. 3

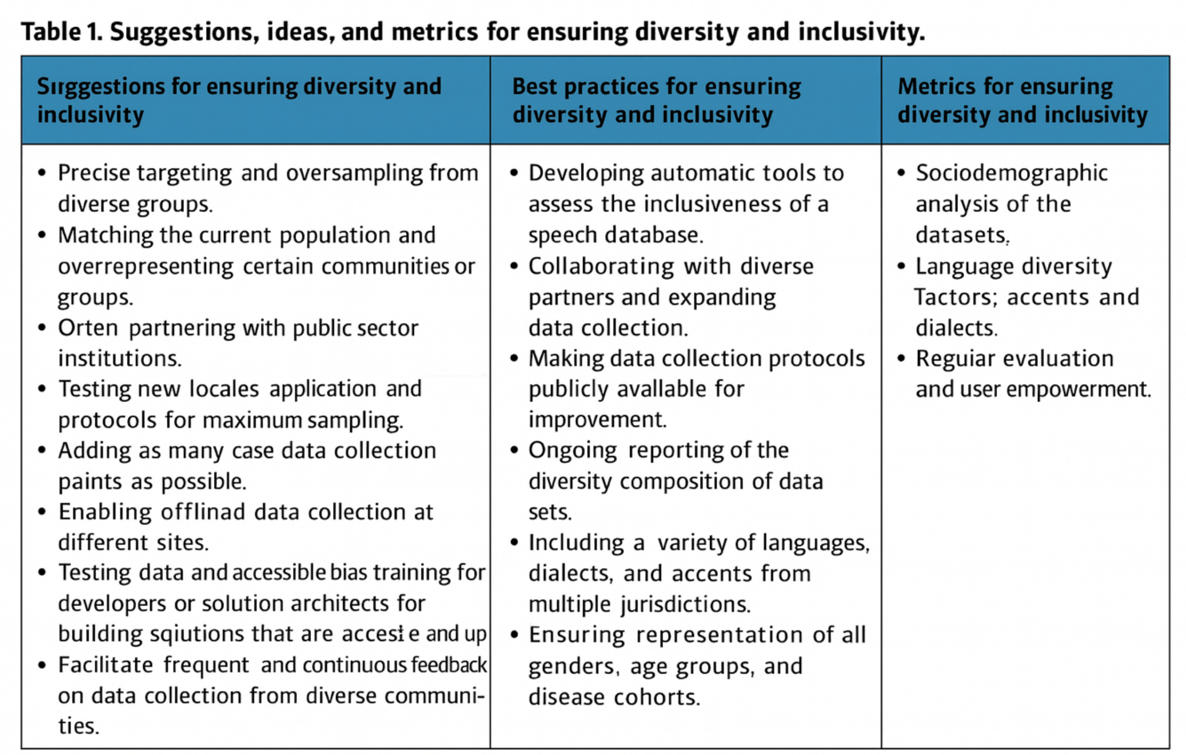


Table 1. Suggestions, ideas, and metrics for ensuring diversity and inclusivity.

Sıggestions for ensuring diversity and inclusivity	Best practices for ensuring diversity and inclusivity	Metrics for ensuring diversity and inclusivity
• Precise targeting and oversampling from diverse groups. • Matching the current population and overrepresenting certain communities or groups. • Orten partnering with public sector institutions. • Testing new locales application and protocols for maximum sampling. • Adding as many case data collection paints as possible. • Enabling offlinad data collection at different sites. • Testing data and accessible bias training for developers or solution architects for building sqiutions that are accesi e and up • Facilitate frequent and continuous feedback on data collection from diverse communities.	• Developing automatic tools to assess the inclusiveness of a speech database. • Collaborating with diverse partners and expanding data collection. • Making data collection protocols publicly avallable for improvement. • Ongoing reporting of the diversity composition of data sets. • Including a variety of languages, dialects, and accents from multiple jurisdictions. • Ensuring representation of all genders, age groups, and disease cohorts.	• Sociodemographic analysis of the datasets, • Language diversity Tactors; accents and dialects. • Reguiar evaluation and user empowerment.

Endometriosis AI mandates: Regular auditing using fairness-aware modelling (demographic parity checks, disparate impact audits), pre-processing (balanced datasets), in-processing (algorithmic adjustments), and post-processing techniques to detect and correct bias by race, ethnicity, socioeconomic status, and geography. (Gwagwa et al., 2022)

AT Framework: Emphasizes that, despite challenges in achieving "perfect data," modelling methods can still introduce bias; comprehensive pre-, in-, and post-processing techniques should be systematically applied and validated against subgroup performance metrics.

Ubuntu Principle: Local Needs as a Prerequisite Framework: Ubuntu ethics requires "discernment": justice is not served by merely adopting AI innovations, but by first asking whether such tools genuinely meet the most pressing needs. Operationally, this translates to: (Ubuntu-based AI framework for healthcare, 2022).

1. ***Needs assessment:*** conduct a participatory assessment of health priorities before any technology is introduced (e.g., expanded healthcare workers and rural infrastructure may be more urgent than AI diagnostics).
2. ***Local problem definition:*** communities, not external experts, must frame the health challenge AI claims to address.
3. ***Alignment with communalism, interdependence, humanism, sharing and compassion:*** technologies must advance collective well-being rather than profit or external agendas.
4. ***Feasibility in local context:*** verify the tool functions in low-bandwidth, limited-electricity environments typical of resource-constrained settings before adoption claims are made. This reframes the evaluation question from "Does this AI work?" to "Does this AI serve *our* community's actual needs, and is it the most equitable investment of scarce resources?"

Theme 4: Governance and Accountability for Inclusion

Why it matters: AI governance papers list “inclusion” as a principle but give no enforcement power shifts, so communities remain advisors rather than decision-makers. (Sarkar, 2025). Only 0.2% of AI-health studies engaged community stakeholders in design, revealing token participation. (Loftus et al., 2024). <10% of AI publications have authors from low-income economies, which shows a global authorship bias (Gwagwa et al., 2022).

Key gaps:

- **Non-binding guidance-** WHO/UN documents are voluntary and lack sanctions (World Health Organization, 2021).

- **Epistemic exclusion**- Global North experts dominate standards; local frameworks such as Ubuntu-based ethics are cited but rarely given authority (Gwagwa et al., 2022).
- **Data colonialism**- Training sets are sourced from high-resource, English-dominant contexts, producing biased models for African, migrant, and rural patients (Sarkar et al., 2025).
- **Infrastructure & capacity**- Low- and middle-income countries (LMICs) report power outages, limited digital literacy, and weak policy frameworks that prevent genuine participation (Loftus et al., 2024).

Regime	**Binding**	**Enforcement mechanism**	**Citation**
WHO ethical guidance (6 principles)	Non-binding	No sanctions	Accelerating UN Sustainable develop
EU AI Act (2024)	Legally binding	Fines up to 6 % of global turnover, suspension of AI systems	Accelerating UN Sustainable development
OECD AI Principles (2019)	Voluntary	No legal enforcement	A unified framework of five principle for AI in Society

African Union Digital-Transformation Strategy (Ubuntu-focused)	Non-binding	No formal penalties; relies on member-state adoption	Reframing Justice in Healthcare AI
CUGH 2024 conference consensus	Advocacy/ethical - no legal force	Recommendations only	Shaping a new era of global health for greater impact

Benchmarks and Accountability

How to operationalize:

Audit existing governance bodies to classify roles (advisory vs. authoritative).

Redesign structures to embed community veto and voting rights.

Pair Capacity-building (training, funding) with the authority transfer, not just skill workshops.

Codify the benchmarks in binding policies; set up independent monitoring panels that report publicly.

Result: Governance moves from “who is invited to the table?” to “who holds the gavel?” ensuring true accountability for inclusive AI in health.

Theme 5: Knowledge Gaps & Future Research

***Regions, populations and health issues that remain under-researched* -** fragile state leadership and finance management in health systems, most evidence missing where need is greatest, Sub-Saharan Africa and the Global South, rural Tanzanian communities are consistently noted as under-researched in AI health work (Odeny et al., 2024). Similarly, health issues affecting displaced or migrant populations, particularly mental-health services, lack robust evidence (Matlin et al., 2024). Women's health, including endometriosis and maternal-care AI tools, is also sparsely studied (El-Bassel et al., 2025). LGBTQ+ mental-health data (Kormilitzin et al., 2023). TB screening, and high-income-country problems such as gun violence or opioid misuse. (Ochasi et al., 2025)

Evidence gaps in inclusive design, governance and evaluation - there are no shared core health system metrics, a lack of guidance on ethical AI design and regulation, weak governance structures of AI in LMICs, missing definitions of "ethically sourced" voice data, a lack of continuous impact assessment, and no standard metrics for inclusivity (demographics, language, dialect). (Bélisle-Pipon et al., 2024), to contextualize these gaps, existing global AI governance regimes show the following status:

Governance regime	**Binding?**	**Enforcement mechanism**	**Evidence for / against**
WHO ethical guidance (6 principles: beneficence, non-maleficence, autonomy, justice, explainability,	Non-binding	No sanctions	identifies WHO principles but notes lack of teeth (WHO, 2021)

inclusiveness)			
EU AI Act (2024)	Legally binding	Fines up to 6 % of global turnover; suspension of AI systems	(Europe's "potential leadership") vs. Global South absent from framing (Matlin et al., 2025)
OECD AI Principles (2019)	Voluntary	No legal enforcement	notes global consensus on principles but "care needed in localising" (Gwagwa et al., 2022)
African Union Digital-Transformation Strategy (Ubuntu-focused)	Non-binding	No formal penalties; relies on member-state adoption	show AU framework lacks enforcement power compared to EU (Ochasi et al., 2025)
CUGH 2024 conference	Advocacy / ethical – no legal force	Recommendations only	notes "lack of input from LMICs limited

consensus (equity-focused)			the scope" (Odeny et al., 2024)

This fragmented landscape means that research and policy guidance remain trapped between voluntary principles (WHO, OECD, AU) and binding mandates (EU). The Global South, where need is greatest, has no equivalent binding framework.

Methodological weaknesses - fragmented, market-focused health system advice, retrospective PRISM modelling limited by proxy variables, small or convenience samples in community AI studies (El-Bassel et al., 2025). Lack of longitudinal follow-up in frontline worker surveys, and black box opacity of many AI models. (Bélisle-Pipon et al., 2024). Only 0.2 % of AI-health studies engaged community stakeholders in design (Loftus et al., 2024).

Research agendas to amplify missing voices - should foreground community-led co-design, decolonial frameworks such as Ubuntu, and participatory evaluation (Gwagwa et al., 2022). Establishing national AI governance bodies, AI-for-Healthcare academies, and mandatory independent equity audits are suggested “fail-safe” policy tools (El-Bassel et al., 2025). Delphi-driven LGBTQ+ participation (Kormilitzin et al., 2023), systems-thinking indices for inclusion (Sarkar et al., 2025). and intersectionality driven women’s health studies.

Underdeveloped “fail safes” and policy tools - social protection and financial catastrophe safeguards remain absent from AI health policies (Alami et al., 2020); AI specific regulatory guidance is lacking in most LMICs (World Health Organization, 2021, Mwogosi et al., 2025); contextualised national AI bodies are rare (Sarkar, 2025); Mwogosi et al., 2025), hallucination reduction via retrieval augmented generation (RAG) is underutilized , explainability tools (SHAP/LIME) remain poorly implemented (El-Bassel et al., 2025; Bélisle-Pipon, Powell, English, et al., 2024), legal frameworks for ethically sourced data are underdeveloped (World Health Organization, 2021), independent equity audits AI systems are infrequently conducted (Gwagwa et al., 2022), monitoring systems for AI malfunctions lack standardization (El-Bassel et al., 2025), proposals for an “AI for healthcare academy” with continuous professional development have not been implemented (Mwogosi et al., 2025), and Ubuntu aligned precautionary principle remain theoretical rather than operationalized in policy (Gwagwa et al., 2022).

To operationalize accountability, the following benchmarks should be embedded in national and international research agendas:

Benchmark	**What it measures**	**Status**	**Target / Accountability**	**Research priority**
Decision-making authority	Community veto over funding, hiring, algorithm release	Advisory-only roles	Community veto rights; breach → project suspension	Co-design audits in 5+ LMIC settings
Impact-weighted representation	Attribution of design changes to specific stakeholder	Demographic head-counts only	Record which stakeholder altered final design; audit	Longitudinal tracking of community influence

	input		quarterly	
Data governance & localisation	Community-defined data-use agreements & local custodianship	External control of datasets	Community-approved agreements; penalties for unauthorised export	Legal review of data sovereignty frameworks
Explainability & bias audit	Mandatory SHAP/LIME explainability & independent bias reports	Transparency statements without tools	Explainability-by-design + bias audit before rollout; non-compliance revokes license	Implementation science trials in rural/migrant settings
Legal enforceability	Binding regulations with sanctions for non-compliance	Mostly non-binding guidelines	National statutes granting oversight committees enforcement	Policy analysis of LMIC statutory gaps

			powers; fines or funding withdrawal	
Epistemic legitimacy Equal voting weight for local knowledge systems (Ubuntu, CHWs)	Equal voting weight for local knowledge systems (Ubuntu, CHWs)	Peripheral consultation	Co-leadership models where local experts share voting power; documented impact on policy decisions	Participatory evaluation of Ubuntu-aligned governance

How local knowledge systems can reshape ethics and governance:

- Ubuntu’s relational autonomy and solidarity replace the individual-centric Western ethic with a people-focused framework that foregrounds interdependence, shared responsibility and communal well-being (Gwagwa et al., 2022).
- Community-centric design for humanitarian mHealth embeds cultural sensitivity, local vocabularies and customary decision-making processes, ensuring that tools are acceptable and usable in crisis-affected settings (Gwagwa et al., 2022).
- Tanzanian AI-health projects show that trust is built when explanations are delivered in locally understandable terms and when consent mechanisms are dynamic, allowing

participants to revise permissions according to community-specific norms (Mwogosi et al., 2025).

- Indigenous-knowledge integration is recommended as a core element of AI policy reform to de-colonise governance structures and align regulatory standards with the epistemic realities of the Global South (Bélisle-Pipon et al., 2024***).***

Policy Response

Norms – Inclusion is anchored in the WHO six-building-block framework (values from Alma-Ata, gender-rights commitments, universal health coverage) (World Health Organization, 2007), and the OECD AI Principles that call for trustworthy, inclusive AI (Matlin et al., 2025). Ubuntu offers a decolonial norm of relational autonomy and solidarity (Gwagwa et al., 2022), while the PRISM-Capabilities model explicitly embeds multi-stakeholder inclusion, transparency and procedural justice (El-Bassel et al., 2025). Gaps are evident: no shared core health-system or inclusivity metrics (demography, language, dialect) (Gwagwa et al., 2022). Guidance on ethical AI design and “ethically sourced” voice data is missing (Bélisle-Pipon et al., 2024). AI-specific regulations are rare in LMICs, and Ubuntu-aligned precautionary principles remain theoretical.

Institutions – Coordination presently relies on WHO’s diagonal links between disease-specific programmes and health-systems advice, and on ministries of finance, education and labour working with donors and private firms. Development partners often create parallel reporting streams that increase transaction costs (World Health Organization, 2007). Reforms needed: establish contextualized national AI governance bodies (Adhikari et al., 2025), strengthen PRISM-driven governance that mandates equity assessment, capacity-building and continuous monitoring, and shift from ad-hoc donor pilots to sustained, ministry-led implementation.

Initiatives – Cooperative platforms include CUGH 2024 (calls for AI regulation and decolonized research), WHO Traditional-Medicine and Digital-Health strategies (Odeny et al., 2024), the AI-Sarosh co-design workshop in South Asia (Adhikari et al., 2025), and AU-backed AI consortia (Ochasi et al., 2025). These bodies often fail to enforce binding standards, most guidelines are non-binding, equity audits are rare, and explainability tools (SHAP/LIME) are poorly applied (Bélisle-Pipon et al., 2024; El-Bassel et al., 2025).

Funding – Current structures reinforce asymmetries: disease-specific aid and out-of-pocket payments skew resources toward conditions favoured by donors, while "who has the gold makes the rules" dynamics concentrate decision-making in high-income firms (Odeny et al., 202; Kalluri, n.d.). Alternative models that could rebalance power are direct LMIC funding streams (e.g., NIH grants to local institutions) (Odeny et al., 2024), pooled regional AI funds with conditional grants tied to local capacity-building, and community-led co-design budgets that require shared voting rights for indigenous knowledge holders (Adhikari et al., 2025).

Conclusion

Global health AI is currently dominated by high-income country institutions, corporations, and donors, systematically excluding the voices of communities most affected by health inequities. This concentration of power, evident in funding structures, knowledge production, regulatory frameworks, and data governance, perpetuates data colonialism and epistemic exclusion. Only 0.2% of AI-health studies engaged communities as co-designers; <10% of AI publications include authors from low-income economies. The result: AI systems that misalign with local priorities, replicate biases, and deepen dependency rather than advance equity.

Meaningful inclusion requires moving beyond consultation to genuine decision-making authority. Evidence demonstrates viable pathways: PRISM-Capabilities operationalizes community co-design across the AI lifecycle with explainability tools (SHAP/LIME) and contestability mechanisms, Ubuntu-based ethics reframe justice around relational autonomy, communalism, and collective well-being rather than individual autonomy, participatory frameworks (Delphi processes, AT design, endometriosis co-creation) embed marginalized voices from problem-definition through evaluation. Local knowledge systems reshape governance: trust is built through culturally understandable explanations, dynamic consent aligned with community norms, and Indigenous knowledge integration.

To operationalize inclusion, the urge is: 1. establish binding national AI governance bodies with community veto authority, 2. fund AI-for-Healthcare Academies for continuous professional development, 3. mandate independent equity audits and bias monitoring, 4. enshrine Ubuntu-aligned precautionary principles in policy, 5. Align funding incentives with co-creation outcomes.

Without structural power-shifts, inclusion remains rhetorical. The future of ethical, equitable AI in global health depends on centring affected communities not as advisors, but as decision-makers.

Appendix A

Exclusion/Inclusion Criteria

<table>
<tr><th></th><th>Included</th><th>Excluded</th></tr>
<tr><td>Article Type</td><td>● Peer-reviewed journal articles
● Peer-reviewed reviews/scoping reviews
● Book chapters from academic publishers (e.g., CRC Press)
● Scholarly books by recognized presses (e.g., Polity) where the focus on AI, power, race, or tech justice
● Grey literature from:
- WHO, UN, OECD, major global health organizations
- Reputable NGOs/ consortia (CUGH, etc.)</td><td>● Wikipedia, blogs, personal websites
● News articles and media commentary
● Random “AI think pieces” on Medium/ Substack
● Non-reviewed students’ papers (can be accessed through Google)
● Pure marketing/industry whitepapers with no methods/evidence</td></tr>
<tr><td>Methodology</td><td colspan="2">Selection of sources was guided by predefined inclusion and exclusion criteria to ensure relevance to global-health governance, equity, and power dynamics. The review included peer-reviewed journal articles, mixed-methods studies, qualitative and quantitative research, conceptual papers, and academic book chapters that examined AI in relation to governance, inclusion/exclusion, or LMIC contexts. High-quality grey literature from major global health institutions such as WHO, UN, OECD, and reputable consortia (e.g., CUGH) was also included. Studies were eligible if they focused on global or LMIC settings, or on high-income countries only when they directly related to global-health policy or marginalized populations. Populations of interest included frontline health workers, women, migrants, LGBTQ+ communities, displaced populations, and other underserved groups.
Sources were excluded when they consisted of blogs, media commentary, opinion posts, unreviewed student papers, corporate marketing whitepapers without evidence, or purely technical AI/ML model papers with no discussion of health systems or governance. Studies focused solely on high-income hospital settings with no equity relevance, non-English publications, and materials produced before 2020 (except one undated UN report) were also excluded.</td></tr>
<tr><td>Geographic Scope</td><td>● Global Analysis of AI in health
● Studies focused on:</td><td>● Studies only about AI for health in rich-country hospital systems with no</td></tr>
</table>

Appendix A

Exclusion/Inclusion Criteria

	- Low- and middle-income countries - High-income countries when they: 1. Affect global health policy, or 2. Directly relate to migrants/refugees/ marginalized populations	relevance to equity, inclusion, migrants, global South or global governance
Population/ Voices	● Frontline health workers ● Patients and communities in LMICs ● Migrants, refugees, displaced people ● Women and gender diverse people ● LGBTQ+ communities ● Policymakers and implementers in global health and digital health ● Purely corporate/industry only perspectives ● Studies focusing exclusively on tech company perspectives without any health or community side	
Time Frame	● 2020 - 2025 ● One undated grey literature and one WHO Guideline from 2007	
Language	● English-language publications	● Non-English articles

Appendix B

Search Strategy

A targeted literature search was conducted between October and November 2025 to identify peer-reviewed and grey literature on whose voices are shaping AI in global health, whose voices are missing, and strategies for inclusive and equitable AI governance in health.

Date of Search	**Database Used**	**Search Terms**	**Total # Articles (Initial Results)**	**After filters or new keywords**	**Total # Articles after 2nd and 3rd search**	**Articles Included in Review for Paper**
October 12, 2025	Carleton Library (Omni)	“artificial intelligence” AND “global health” AND equity	193	• Peer Reviewed Journals • Articles • Book Chapters • Books	• 158	11
October 17, 2025	Carleton Library (Omni)	“AI governance” AND (LMIC OR ‘low resource’) AND “health”	5			5
	Google Scholar	“AI governance” AND (LMIC OR ‘low resource’) AND “health”	1060	• “AI governance” AND (LMIC OR ‘low resource’) AND “health” “AND Women” • Initial scan of titles • Reviewed Keywords of the articles	• 670 • 40 • 27 • 14	10

				- Read abstracts		
October 18, 2025	Google Scholar	“AI inclusion” AND “global south” AND healthcare”	61	- Scanned the titles - Articles with PDF links - Articles with active links	- 39 - 15 - 16	7
October 22, 2025	Google Scholar	“algorithmic bias” AND “health disparities”	3660	- “algorithmic bias” AND “health disparities” AND “Inequity” - “algorithmic bias” AND “health disparities” AND “Inequity” AND “LMICs” - “algorithmic bias” AND “health disparities” AND “Inequity” AND “LMICs” AND “Frontline Workers”	- 634 - 66 - 26	9
October 23, 2025	Carleton Library (Omni)	community-engaged AI” OR “participatory AI”	5,023	- community-engaged AI” OR “participatory AI” AND “Community Involvement” - community-engaged AI” OR	- 364 - 191 - 189	10

				“participatory AI” AND “Community Involvement” AND “Scoping” ● community-engaged AI” OR “participatory AI” AND “Community Involvement” AND “Scoping” AND “LMIC”		
	Google Scholar	community-engaged AI” OR “participatory AI”	14,800	● community-engaged AI” OR “participatory AI” AND “Community Involvement” ● community-engaged AI” OR “participatory AI” AND “Community Involvement” AND “Scoping” ● community-engaged AI” OR “participatory AI” AND “Community Involvement” AND “Scoping” AND “LMIC”	● 14500 ● 2,970 ● 78	15
	PubMed	“community-engaged AI” OR	17			1

		“participatory AI”				
October 25, 2025	Carleton Library (Omni)	“artificial intelligence in healthcare” AND “low-resource settings”	2			2
	Google Scholar	“artificial intelligence in healthcare” AND “low-resource settings”	1,440	• “artificial intelligence in healthcare” AND “low-resource settings” AND “Development”	• 1,400	20 Found the same article on the first and second Search pages
October 26, 2025	Carleton Library (Omni)	“Artificial Intelligence” AND “South Asia”	2,073	• “Artificial Intelligence” AND “South Asia” AND "equity"	• 20	
	Google Scholar	“Artificial Intelligence” AND “South Asia”	81,600	• “Artificial Intelligence” AND “South Asia” AND "equity"	• 14,800	12 Found same articles on the first and second Search Pages
	PubMed	“Artificial Intelligence” AND “South Asia”	35	• “Artificial Intelligence” AND “South Asia” AND "equity"	• 6	6

October 28, 2025	Carleton Library (Omni)	voice AI” AND “ethical considerations” AND "Health"	84	● voice AI” AND “ethical considerations” AND "Health" AND “perspective”	● 19	10
	Google Scholar	voice AI” AND “ethical considerations” AND "Health"	309,000	● voice AI” AND “ethical considerations” AND "Health" AND “perspective” ● Title reviews ● Abstract review	● 220,000 ● 200 ● 15 Overwhelming Results	10
	PubMed	voice AI” AND “ethical considerations” AND "Health"	4 Different Articles from other search databases			2
Oct 30, 2025	Carleton Library (Omni)	“AI ethics” AND “Justice"	357	● “AI ethics” AND “Justice" AND "Example"	● 18	
	Google Scholar	“AI ethics” AND “Justice"	28,300	● “AI ethics” AND “Justice" AND "Example"	● 24,600	
	PubMed	“AI ethics” AND “Justice"	28	● “AI ethics” AND “Justice" AND "Example"	● 3 Different articles - not related	8
Nov 1, 2025	Carleton Library (Omni)	“AI ethics” AND “health justice”	7			5

	Google Scholar	“AI ethics” AND “health justice”	2,450	• “AI ethics” AND “health justice” AND “Health” • “AI ethics” AND “health justice” AND “Health” AND “Education” • Review of Titles • Review of Abstracts	• 1,870 • 600 • 50 • 15	10
November 5, 2025	Carleton Library (Omni)	“algorithmic bias” AND "Health"	760	• “algorithmic bias” AND "Health" AND "racist"	• 5	5
	Google Scholar	“algorithmic bias” AND "Health"	36,700	• “algorithmic bias” AND "Health" AND “Racist” • “algorithmic bias” AND "Health" AND "racist" AND "Gender Inequity"	• 3,820 • 20	11
November 6, 2025	Carleton Library (Omni)	“LGBTQ+ inclusion” AND “AI” AND "Health"	4	• “LGBTQ+ “Voices” AND “AI” AND "Health"	• 2	4
	Google Scholar	“LGBTQ+ inclusion” AND “AI” AND "Health"	1	• “LGBTQ+ ”Voices” AND “AI” AND "Health"	• 5	5
November 7, 2025	Carleton Library (Omni)	AI power dynamics” AND “marginalized communities”	17	• AI power dynamics” AND “marginalized communities” AND	• 2	10

				"Healthcare"		
	Google Scholar	AI power dynamics” AND “marginalized communities”	171,000	• AI power dynamics” AND “marginalized communities” AND "Healthcare" • AI power dynamics” AND “marginalized communities” AND "Healthcare" AND "Migrants" • AI power dynamics” AND “marginalized communities” AND "Healthcare" AND "Migrants" AND "tools" • Review of titles • Review of Abstract	• 48,700 • 17,300 • 12,300 • 50 • 18	8
November 12, 2025	Carleton Library (Omni)	“AI” AND “humanitarian action”	38	• “AI” AND “humanitarian action” AND “Health”	• 4	10
	Google Scholar	“AI” AND “humanitarian action”	10,100	• “AI” AND “humanitarian action” AND “Health” • “AI” AND “humanitarian action” AND "health" AND "Inequity" • Review of the titles	• 7,170 • 358 • 40 • 10	10

				● Review of Abstracts		
Nov 10, 2025	WHO Website	“artificial intelligence governance”, “digital health strategy”, “equity”	323	● artificial intelligence governance”, “digital health strategy”, “equity” AND "Ethics"	163	3

Appendix C

Acronym List

Acronym	Full Meaning
AI	Artificial Intelligence
AT	Assistive Technology
AU	African Union
CAB	Community Advisory Board
CHW	Community Health Worker
CUGH	Consortium of Universities for Global Health
EU	European Union
GPT-4	Generative Pre-Trained Transformer 4
HCW	Health Care Worker / Health Worker
HIC	High-Income Country / High-Income Countries
IEEE	Institute of Electrical and Electronics Engineers
LGBTQ+	Lesbian, Gay, Bisexual, Trans, Queer/Questioning, and others
LIME	Local Interpretable Model-agnostic Explanations
LMIC	Low- and Middle-Income Country / Low- and Middle-Income Countries
mHealth	Mobile Health
NDIA	National Disability Insurance Agency (Australia)
NGO	Non-Governmental Organization
OECD	Organisation for Economic Co-operation and Development
PARQAIR-MH	Participatory Queer AI Research for Mental Health
PRISM	Practical, Robust Implementation and Sustainability (Capabilities Model)
PWD	People with Disabilities
RAG	Retrieval-Augmented Generation
SDG	Sustainable Development Goal / Sustainable Development Goals
SHAP	SHapley Additive exPlanations
SRMH	Sexual and Reproductive Mental Health
SUS	System Usability Scale
TB	Tuberculosis
UN	United Nations
US	United States
WHO	World Health Organization

Appendix D

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