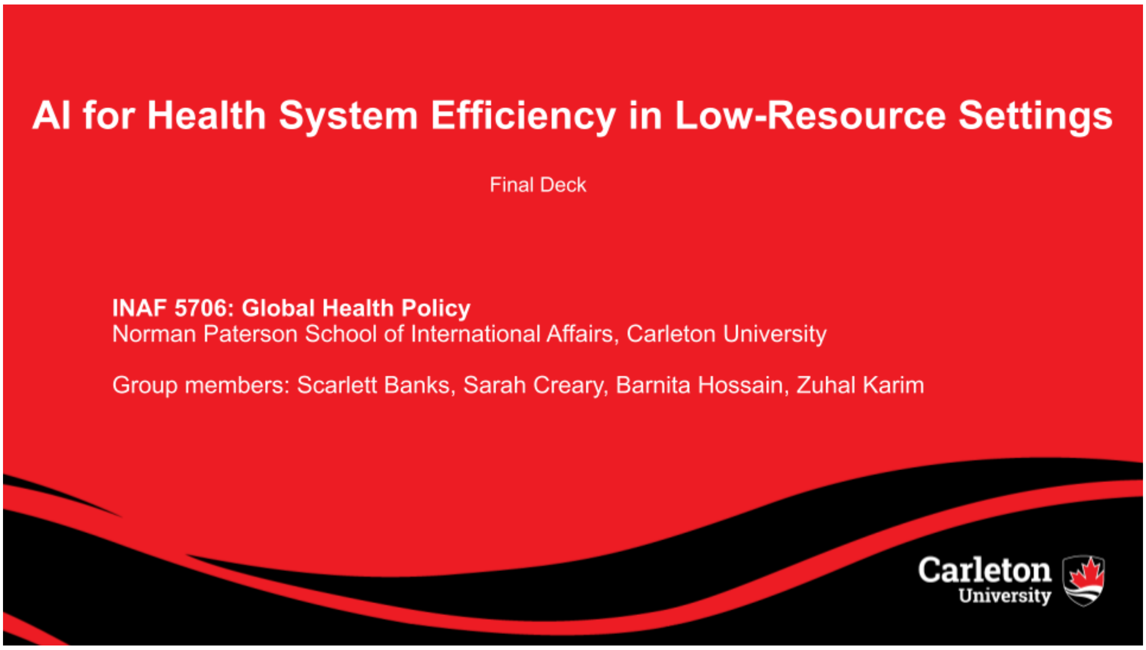
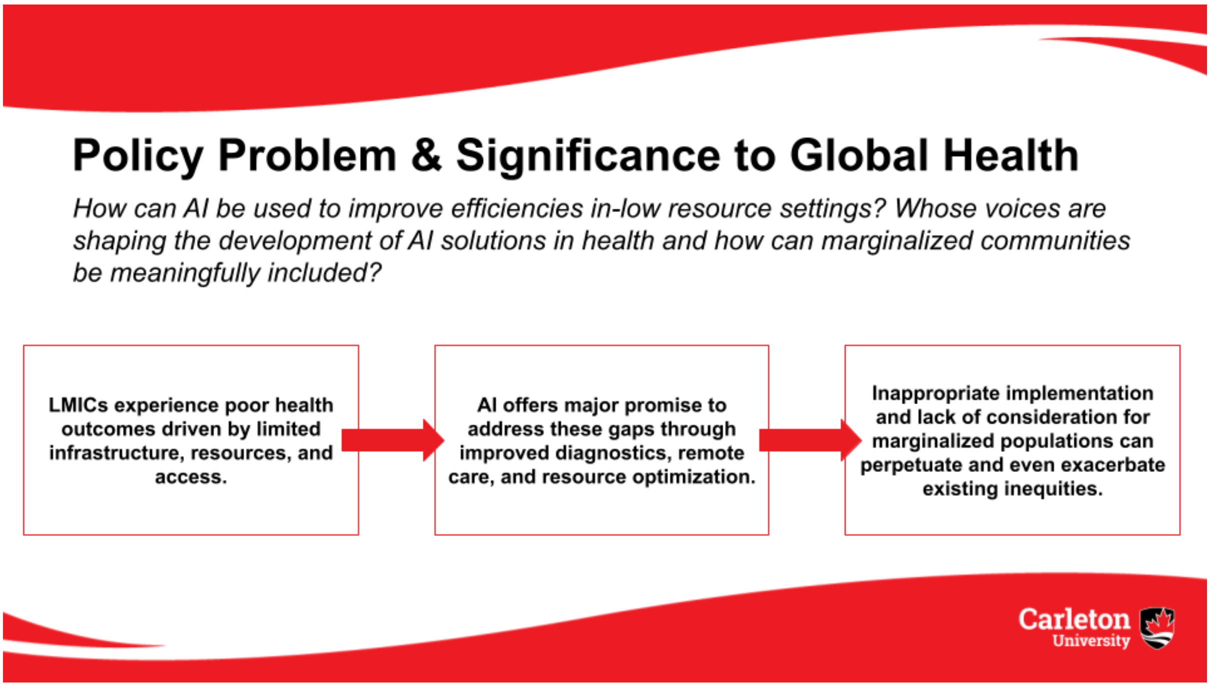
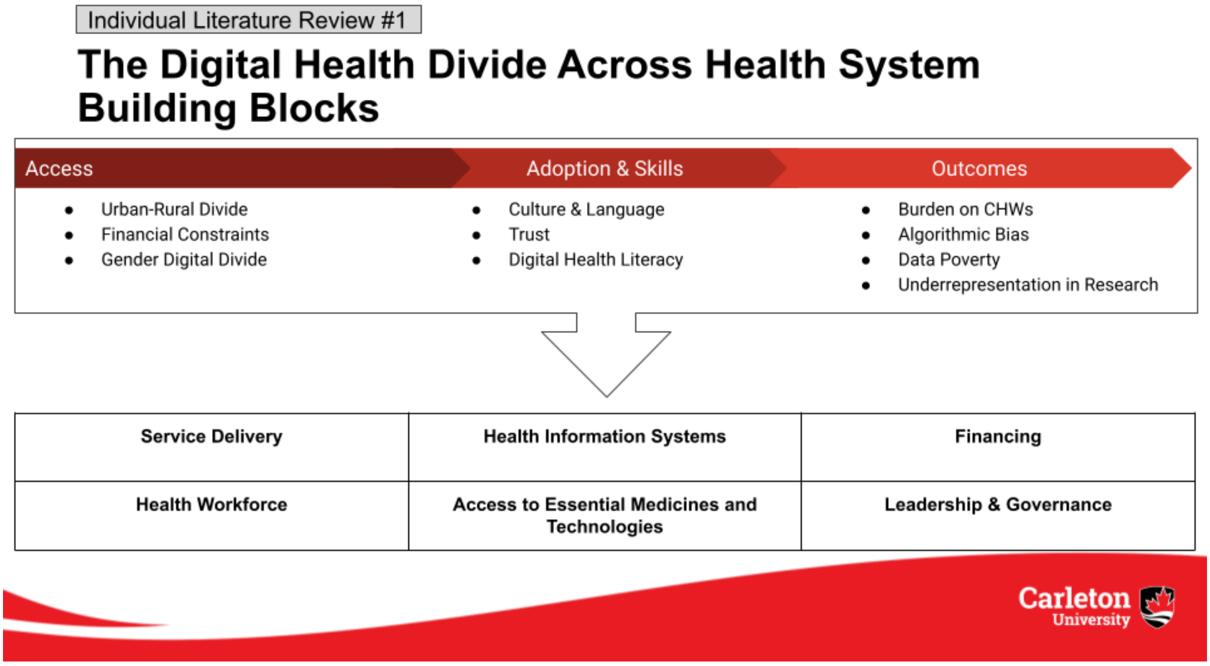


- The purpose of this meeting is to present our final findings following the completion of our comprehensive literature reviews.
- The following research question was addressed: How can AI improve efficiencies in health systems (refer to the building blocks).Whose voices and perspectives are shaping the development of AI solutions in health, and how can communities most affected by inequities—such as women, youth, displaced populations, and persons with disabilities—be meaningfully included in design, governance, and evaluation of global health-related AI innovations?
- The question was broken up into four topics for the literature review: (1) the digital divide across health system building blocks; (2) maternal and reproductive health as a specific application of these building blocks; (3) the absence of marginalized voices and strategies for inclusive AI; and (4) the policy and governance frameworks needed for equitable and ethical AI integration in LMICs.



- Low-resource settings are characterized by high disease burdens and vast healthcare disparities that result from complex systemic challenges, and the implementation of AI has the potential to build efficiencies to improve these healthcare systems and thus health outcomes (Sylla, Ismaila, & Diallo, 2025).
- The majority of AI has been developed and tested in high-income countries, and their arbitrary application to low-resource settings without holistic consideration of contextual factors can exacerbate rather than solve health inequities and disparities, disproportionately affecting marginalized populations.
- Context specific AI design and implementation is imperative in working towards global health equity (Wibowo, 2025; Wong, Bermudez-Cañete, Campbell, & Rhew, 2025).



- Focusing on the digital divide reflects the reality that technologies designed in high-income countries encounter substantial barriers in access and infrastructure when introduced into low-income settings, which affects their implementation and uptake. This digital divide exists not only between HICs and LMICs, but also within LMICs themselves, mirroring existing social inequalities.
- Social disadvantage is associated with lower use of digital technologies, meaning digital health interventions often disproportionately benefit more privileged groups (Western et al., 2025; König et al., 2023). Marginalized populations, who already experience inequitable health outcomes, face the greatest barriers to digital access and are therefore least able to benefit from these interventions (Sylla et al., 2025; Raza et al., 2025).
- The digital health divide which can be separated into 3 levels; disparities in access to and infrastructure for health technology, disparities in the skills required to navigate and interact with health technology, and disparities in the outcomes derived from digital technologies (Western et al., 2025).
- Service Delivery: Improve accessibility through translation tools and visuals, develop contextualized models using Retrieval-Augmented Generation (RAG), co-design with CHWs, use Reinforcement Learning from Human Feedback (RLHF) with pre-deployment bias testing, ensure transparency, and prioritize digital health literacy (Lima et al.; Wong et al., 2025; Figueroa et al., 2023; Choi, 2025).
- Health Workforce: Empower CHWs and pharmacists as trusted navigators, ensure role protection and fair compensation, provide tailored AI training, and build local technical capacity (Sylla et al., 2025; Tensen et al., 2025; Jonayed & Rumi, 2024).
- Health Information Systems: Invest in robust infrastructure, data governance, centralized repositories, interoperability standards, ethical data practices, continuous IT support, and development of localized datasets (Wong et al., 2025; Wibowo et al., 2025; Koehle et al., 2022).
- Access to Medicines & Technologies: Expand digital inclusion through subsidized devices, affordable internet, low-bandwidth-compatible tools, and establish secure, ethical guidelines for the use of informal platforms (Sylla et al., 2025; Alnasser et al., 2025; Thakur et al., 2025).
- Financing: Develop sustainable financing models, regulate pricing and uncompensated care, and use public–private partnerships to stabilize implementation (Wong et al., 2025).
- Leadership & Governance: Ensure political stability and institutional trust, create ethical AI roadmaps, adapt monitoring metrics to local contexts, support cross-sector collaboration, and promote global knowledge sharing (Wibowo et al., 2025; Thakur et al., 2025; Maaß et al., 2024; König et al., 2023).
- There remains a lack of actionable policy and program direction, limited ethical and regulatory consideration of public–private partnerships, minimal discussion of AI's role in secondary and tertiary care, and an overall absence of systems-level thinking throughout the literature.

Individual Literature Review #2

Maternal Care and SRHR Across Health System Building Blocks

Findings

- Improved diagnostics
- Higher antenatal care turnout
- Access to SRHR information + services
- Reduced digital literacy barriers

Gaps

- Lack of real-world implementation
- Limited funding/finance structures
- Unequal access to technology
- Lack of local participation
- Lack of SRHR governance + frameworks

Carleton University

- Analyzing the use of AI to enhance maternal care and SRHR in low- and middle-income countries (LMICs) revealed that AI does not operate in a vacuum; its effectiveness fundamentally depends on the strength of underlying health system structures, governance, financing, and infrastructure.
- Findings, for some sections, focused more on what's missing and what must be implemented in order for AI to enhance maternal care and SRHR.
- **Access to technology and medicines:** AI-assisted ultrasound and diagnostic algorithms to improve the detection of high-risk pregnancies and enable earlier interventions (Izadnegahdar, 2024; Fernandez et al., 2020); AI-driven telemedicine (mHealth, chatbots) for appointment adherence, sexual health education, context-sensitive guidance, and triage (Wang et al., 2022; Jacaranda Health, 2023). Natural language processing (NLP) is a sub-set of AI used to overcome language barriers (Wang et al., 2022).
- **Health financing:** Incorporate AI tools for maternal care and SRHR into universal health coverage (UHC) frameworks to reduce out-of-pocket payments and cost of medicines (Banke-Thomas et al., 2021; Debie et al., 2025); Increase both domestic and donor funding to improve service availability and quality (Sully et al., 2024).
- **Leadership & governance:** Effective AI adoption requires clear regulatory standards and mechanisms for meaningful community engagement to advance rights-based and equitable health outcomes (Islam et al., 2024; Saleh et al., 2025).
- **Gaps:** Many studies remain in pilot phase and do not represent real-world implementation; limited funding and finance structures; unequal access to technology and gender misrepresentation (Wang et al., 2022); lack of local participation in LMICs in the design of governance framework, also points to a broader lack of a "legal" framework for the safe and ethical use of AI (Alami et al., 2020).

Individual Literature Review #3

Who Shapes AI in Global Health: Evidence & Gaps

Actor (Who)	Evidence (What They Do)	Gap/Impact
Big Tech (e.g., Google/DeepMind)	Models trained on HIC datasets & deployed globally	Poor LMIC performance
Elite Universities (MIT, Oxford)	Produce most AI research	Knowledge production dominated by Global North
Donors (Gates Foundation)	Fund AI projects aligned with donor priorities	Misaligned with community needs
Global Bodies (WHO)	Issue ethical principles for AI	No legal enforcement

Carleton University

In my literature review, I learned that who shapes AI and it's development in global health. The groups that consistently dominate the global health AI ecosystem, and each leaves a very specific gap in low-resource settings.

Big tech companies (e.g., Google, DeepMind): these companies train AI models almost entirely on datasets from high-income populations.

Example: Dermatology AI, which performs well on lighter-skinned patients but misclassifies conditions on darker skin because the training data excluded African populations (Sarkar, 2025).

This leads to poor transferability, misdiagnosis and system failures when the same tools are deployed in rural clinics with weak connectivity.

Elite Universities (e.g., Massachusetts Institute of Technology, Oxford) produce most AI research, and less than 10% of AI papers include authors from low- and middle-income economies. This creates epistemic exclusion.

Example: Tanzania, primary care clinics still rely on paper records, but many AI models developed in Western universities assume electronic health records and stable electricity. These assumptions do not reflect LMIC realities, yet they shape global benchmarks anyway (Sarkar, 2025).

Donors (Gates Foundation): Donors fund AI projects based on their own priority areas. **Example:** AI tools for sexual and reproductive health, which donors heavily support. But studies show these tools often require constant internet access, making them unusable in rural areas with 50% or lower mobile subscription rates (Lima et al., 2025).

Global Bodies (WHO): issues ethical principles for AI, but these are non-binding, with no enforcement. We see the **impact in maternal-care AI tools** that pass global ethical review but still fail in local clinics because the guidelines don't require real-world testing in low-infrastructure settings.

So inequities persist even when the principles look strong on paper (WHO, 2021).

Conclusion: Together, these patterns mirror data colonialism, power, and data flow outward, while gaps and inequities remain in local health systems.

Notes: Most affected communities are also the ones most systematically excluded from AI development. These include women in low-resource settings, frontline community health workers, LGBTQ+ individuals, rural populations, and researchers from Africa, South Asia, and Latin America. They are rarely consulted, and rarely given decision-making power (Gwagwa et al., 2022; kormilitzin et al., 2023; Mwogosi, 2025; Lima et al., 2025; Sarkar, 2025).

The consequences of this exclusion are clear and well-documented: AI chatbots deployed for sexual and reproductive health in South Asia and Sub-Saharan Africa gave **culturally unsafe, generic advice**, causing users to stop using them altogether. GBV survivors avoid AI-enabled triage systems because biometric data collection feels like surveillance, especially in humanitarian contexts where data extraction mirrors data-colonial practices.

Algorithms trained almost entirely on Western datasets **misdiagnose African patients**, because they fail to recognize local epidemiology. In Tanzania, maternal-health algorithms missed about **30% of locally relevant risk factors**, directly increasing the risk of harmful outcomes.

We also see major breakdowns when AI tools assume conditions that simply don't exist in rural clinics. Tools that require constant internet connectivity fail immediately in settings where power outages are routine and mobile subscription rates sit below 50%. Frontline workers in rural Malawi and Tanzania abandoned several AI tools because they weren't usable offline, leading to diagnostic delays of malaria, TB, and maternal complications.

Voice-AI systems designed without local linguistic input misinterpreted distress signals, accidentally exposing sensitive information in contexts where privacy breaches can lead to social exclusion or violence (Adhikari et al., 2025; Matlin et al., 2025; Mwogosi, 2025; Belisle-pipon et al., 2024).

All of this reflects a deeper structural problem: these communities are not represented in AI design or governance. The literature shows that **only 0.2%** of all AI-health studies included community stakeholders at the design stage. When women, rural patients, CHWs, or marginalized groups are missing from datasets and design teams, the tools built for them are inaccurate, unsafe, and mistrusted. This absence isn't random; it's a form of **epistemic injustice**, where certain voices, knowledge systems, and lived experiences are systematically excluded. It also reinforces **data colonialism**, because data flows out of LMIC contexts, but decision-making and benefits remain concentrated in the Global North (Loftus et al., 2024; Gwagwa et al., 2022; Ochasi et al., 2025).

Data biases: Locally-sourced data is a key element in deploying and integrating AI in low-resource settings (Williams et al., 2024). Health data poverty exists when there is inadequate representation of diverse groups in healthcare datasets, and this limits their proficiency and benefits in LMICs (Lanyi et al., 2024)

Ethical Challenges: Contextual bias; This challenge is characterized as the issue of AI systems basing predictive abilities and models on the data from HICs (Lopez et al., 2022).Scholars have indicated that to enforce ethical deployment of AI, structural barriers must be addressed before integration, as it becomes unethical to deploy AI when there is predictable harm on communities (Hailu & Haddad, 2025).

Infrastructural Challenges: In LMICs there are varying degrees of access, and poor connectivity is an infrastructural barrier that exists in many areas (Lopez et al., 2022). Infrastructure and technology limitations can lead to limited access and affect the capacity in which individuals and groups can utilize AI (Oladipo et al., 2024). A lack of ICT infrastructure, which includes all of the physical and virtual resources, is persistent in LMICs (Oladipo et al., 2024).

Global Organization's Policy Response:

<u>WHO Global Strategy on Digital Health: </u>The WHO has committed to both developing and promoting frameworks for digital health, and supporting other countries in enforcing these standards within their own AI use in health systems (World Health Organization, 2021b).

<u>WHO Ethics and Governance:</u>The WHO's Ethics and Governance of Artificial Intelligence for Health, has developed a policy framework that sets out to determine how AI in health should be governed and regulated (World Health Organization, 2021a).

<u>UNDP Human Development Report :</u>The UNDP has highlighted that AI's social effects are also influenced by the institutions, power structures, and policies within the areas they are employed (UNDP, 2025). Humans also have a role in regulating the design and deployment of AI to ensure that AI will have positive effects on health systems (UNDP, 2025).

<u>OECD Framework for the Classification of AI Systems: </u>The development of the framework has considered that there are various advantages and risks of AI systems and there are variations that require there to be different policy approaches (OECD, 2022).The OECD does not specifically focus on low-resource settings and LMICs, though the organization places strong emphasis on context specific questions, looking at who is affected and how operational the AI systems are in constrained environments (OECD, 2022).

Gaps: At a global level, there is significant work being conducted in creating frameworks to guide the ethical implementation of AI and governing its use. While the frameworks that have been created are good in theory, they are currently largely prescriptive, and have not been used in practice. It is difficult to determine the potential positive effects on communities and specifically in low-resource settings, as states are newly adopting these frameworks. Due to the new global environment, and shrinking funding, low-resource settings and LMICs who rely on funding have prematurely been forced into self-reliance for their own national development. We must now ask what is next for development, and how will this impact AI integration, and its equitable and ethical use.

- **Focus on practical implementation of their governance/regulatory frameworks:**
    - AI is in an early stage of implementation within low-resource settings and LMICs, as seen within current research.
        - The leading organizations are creating a strong foundation that can be built upon and implemented within states and low-resource settings, to ensure AI is being used in the most ethical and equitable capacities.
- **Ensuring cultural relativity and transparency in AI integration:**
    - Due to the vast capabilities of AI, there have been challenges in regards to accuracy, consistency, and data accessibility (Lopez et al., 2022). Researchers have found that robust planning and environments are needed for proper AI integration, that includes training and standards that implement policies concerned with privacy, security, ethics, and equity, amongst many other areas (Lopez et al., 2022). The failure to account for socio-cultural contexts, will not allow for AI to be integrated and operated at its maximum capability (Lanyi et al., 2024).
- **Sustained investment in infrastructure to assist in AI integration in LMICs:**
    - Researchers have highlighted the need for international organizations to support the expansion of healthcare technology to LMICs, and help ensure the affordability of health specific software (Adedinsewo et al., 2025).
- **Advocacy for development aid:**
    - The future of AI integration is unknown, and likely to see drastic changes due to the developing budget cuts and weakening of donor funding to global health and development across the board.
    - Moving forward, a shift in national funding towards domestic health programs could be a move made by LMICs and low-resource settings, in order to continue with AI integration and use.
    - Costs associated with infrastructure for AI integration also pose a threat, as previous funding is waning.
    - While AI integration has the capacity to strengthen health systems and care for both LMICs and HICs, the cuts to global health and development aid are sure to shift priorities in different regions.

Recommendation on Strategies including these groups. There are several practices that support meaningful inclusion of inequity-affected groups, but **two stand out most clearly in the evidence**.

Co-design: Loftus et al. (2024) found that only **0.2%** of AI-health studies involved community stakeholders, yet those few produced tools that were **more generalizable and less biased**, especially in low-resource settings. This tells us that when these groups help shape AI from the beginning, the tools become safer, culturally appropriate, and more accurate. In contrast, when design happens in the Global North, algorithms miss local realities, like the Tanzania case where maternal-health tools **missed 30% of local risk factors** because midwives were never consulted (Mwogosi, 2025).

Governance that centres local ownership: Governance frameworks that emphasize data sovereignty, participatory oversight, and ethical accountability are essential to preventing harm to inequity groups. They make sure AI aligns with local norms, protects privacy, and supports frontline workers rather than undermining them.

1. Ubuntu-Guided Regional Ethics Committees (Africa)- A governance model where patient advocates, nurses, and community health workers share real decision-making power to ensure AI reflects African communal values and prevents data colonialism (Ochasi et al., 2025).

2. Community-Defined Equity Audits in the PRISM-Capabilities Model- A system where communities, not external experts, co-define which disparities AI must track and how errors are interpreted, creating continuous, locally governed fairness oversight (El-Bassel et al., 2025).

Both mechanisms shift power from external experts to the people who will live with the technology, thereby improving relevance, trust, and equity of AI-enabled health solutions.

Overall general recommendation:

Invest in energy infrastructure to power AI systems sustainably (in rural/underserved areas).

- AI fails when it is not co-designed with the people it is meant to help. SRHR tools need trust, cultural sensitivity, and legitimacy – especially in conservative contexts. What this recommendation implies:
    - Fund projects where local women (adolescents, rural, marginalized groups) shape problem definition, design, and testing.
    - Require community advisory boards
    - Invest in qualitative research
    - Integrate gender experts

- AI for SRHR sits at the intersection of gender norms, privacy, criminalization, stigma, and state surveillance. In many LMICs, the biggest barrier is not the technology, but rather the social and legal risks of using it. What this recommendation implies:
    - Comparative studies on SRHR + AI (e.g., abortion info, minors, consent)
    - Fund research on privacy threats (e.g., partner/family surveillance, device sharing)

- IDRC should continue and deepen its support for AI-for-SRHR research/regional SRHR research networks, particularly in conservative contexts to ensure ongoing development of safe, locally relevant, and rights-based digital solutions.

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