

Siloization in Artificial Intelligence (AI) and Global Health Research & Development (R&D)

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Group 3 Presentation:

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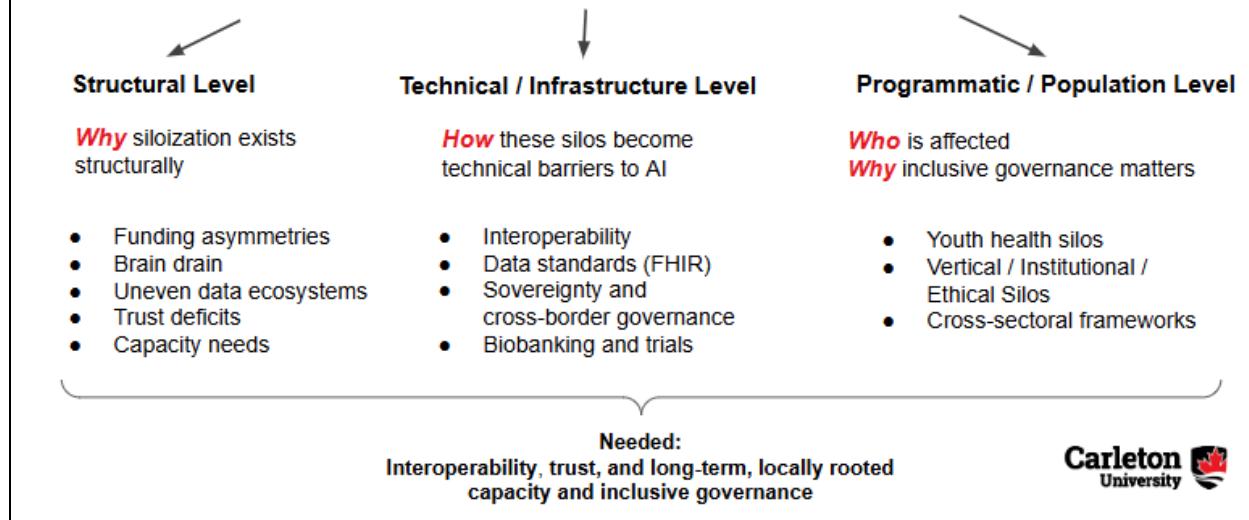
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Research Question and Approach

What are the gaps in research agendas and protocols, and 'siloization' of AI and global health research that hinder alignment of global health goals with AI technologies?



Research Question: *"What are the gaps in research agendas and protocols, and the siloization of AI and global health research, that hinder alignment of global health goals with AI technologies?"*

Over two months of research, the collective understanding of this question evolved and each group member ended up taking a distinct but complementary approach to the question. Each member explored a different case study, but always within LMIC settings, especially Africa.

Broadly speaking, the group looked at the gaps and silos from a structural level; technical and infrastructure level; and a programmatic or population level.

The research was structured as follows:

- Why silos exist (structural level);
- How these silos break technical systems (technical / infrastructure level);
- Who is affected (programmatic / population level).

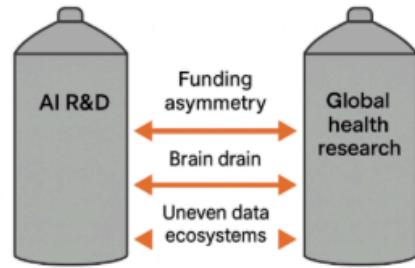
Despite different case studies, the project converges on shared themes: interoperability, trust, and long-term, locally rooted capacity building.

Theme 1: Structural Divide between AI & Global Health Research

Siloization separates AI development from global health needs

AI and global health research often operate in distant silos:

- Industry-led AI R&D driven by private investment and proprietary datasets.
- Global health research grounded in public-sector and academic priorities.



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This first theme explores foundational reasons for why AI and global health R&D have evolved in parallel but disconnected spaces.

The literature frames this siloization as a divide between industry-led AI research, driven by private investment and proprietary data, and epistemic global health communities, which operate primarily in public and academic settings with these two silos often having different priorities, making sustained collaboration difficult.

Key Structural Drivers:

1. **Funding asymmetry:** AI research benefits from substantial private-sector investment, whereas global health research often faces financial constraints. This tends to concentrate technical development capacity in industry settings.
2. **Brain drain (academia-to-industry):** Skilled researchers move toward higher-paying industry roles, leaving fewer experts in public health and academic institutions who can guide or adapt AI tools for health-system contexts.
3. **Uneven data ecosystems:** Industry generally controls large proprietary datasets, while global health and LMIC researchers often work with smaller, static, or fragmented datasets. This limits independent validation and can hinder the creation of tools tailored to specific health contexts.

These structural conditions don't just separate institutions - they shape who has power, capacity, and control over AI development.

Trust as an important determinant of AI utility

- Trust is a key determinant of how technologies are adopted in global health settings
- Sources of distrust:
 - **Opacity:** Black-box models and limited visibility into data or development processes.
 - **Reliability:** Tools trained on non-representative datasets often underperform in LMIC contexts.
 - **Accountability:** Weak governance and unclear responsibility for errors or risks.

Inclusion advances trust by improving 1) **contextual relevance**, 2) **legitimacy**, and 3) **transparency**, counteracting the effects of siloization.

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Across the literature, trust appears as a key determinant of whether AI tools can be used effectively in many contexts including global health. Even technically sophisticated systems may not be adopted if users lack confidence in their fairness, accuracy, or oversight. AI's innovative potential is not enough to enamour trust. Distrust in AI usually comes from three main sources:

1. **Opacity:** Black-box nature of models limit understanding of how decisions are made, and siloization can intensify this by restricting access to data and development processes.
2. **Reliability:** Models trained on non-representative datasets may perform inconsistently in LMIC settings, reducing confidence in their outputs.
3. **Accountability:** When governance structures lag behind technological development, affected communities may feel uncertain about risk management and oversight.

Several sources indicate that trust is often stronger when people who will use or be affected by AI systems are meaningfully involved in their development or governance. Inclusion can support trust in a few ways:

- **Contextual relevance:** local clinicians, researchers, and communities understand their health-system realities, which can help ensure that tools fit local constraints, workflows, and needs.
- **Legitimacy and social acceptance:** tools developed entirely outside the settings where they will be used may feel disconnected from local priorities.
- **Transparency and accountability:** participation can provide more visibility into how decisions are made and who is responsible for ensuring safety. Since siloization often reduces transparency, inclusion may help reintroduce a sense of oversight.

AMR Case Study

Why?

AMR is inherently cross disciplinary



AI shows promise in its use for AMR surveillance, even in low resource settings

Takeaway: Long-Term Capacity-Building Matters

- In Sub-Saharan Africa, both AMR and AI expertise are scarce.
- Emerging initiatives emphasize **long-term, locally grounded capacity**, not short-term external consultancy:
 - Capacity Accelerator Network (CAN)
 - Fleming/Deep Mind Initiative: Extended fellowships supporting continuous AI-AMR research and local leadership.
- Capacity-building can advance trust by embedding sustained expertise, contextual understanding, and shared ownership within local institutions/actors.

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In this theme, the case study undertaken was an African-focused AMR case study which illustrated how trust may be strengthened by building long-term, stable career pathways that help keep expertise within local institutions.

AMR as a global health issue is inherently interdisciplinary and AI has shown promise for addressing AMR, particularly through surveillance, even in LMICs.

Sub-Saharan Africa faces shortages of AMR and AI specialists, and both fields are affected by outward migration of skilled researchers. A number of emerging initiatives are attempting to address this by supporting sustained, locally grounded expertise.

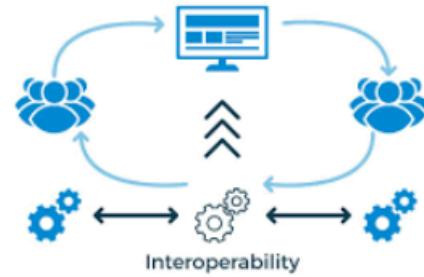
A growing theme across AI-AMR efforts in African global health efforts is a shift toward long-term, locally grounded capacity building, rather than short-term external consultancy. For example, the Capacity Accelerator Network (CAN), which IDRC is involved in funding structures multi-year opportunities for early-career data scientists. Another example is the DeepMind–Fleming Initiative which invests in extended fellowships focused on AI-AMR research, enabling continuity, and the emergence of local leadership.

These case studies provide examples of long horizon capacity-building that are fostering trust to ensure AI systems are developed with sustained local expertise, contextual understanding, and shared ownership.

Theme 2: Communication and Interoperability

AI cannot be ethically or effectively integrated into clinical trials in low-resource settings due to:

- Conflicts between AI data needs + data sovereignty laws
- Fragmented, low-capacity digital infrastructures
- Lack of harmonized data + communication protocols



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The second theme focuses on how these silos manifest technically when it comes to using AI for clinical health research trials.

Clinical trials in low-resource settings are essential for generating evidence that reflects the populations most affected by disease.

But effective AI depends on harmonized, high-quality data and stable protocols.

Right now, those conditions aren't in place, so AI cannot be successfully implemented in multi-country clinical trials in Africa because interoperability and sovereignty rules contradict the technical requirements of AI.

Why Clinical Trials Reveal Gaps & Siloization

- Clinical trials require coordinated, multi-country data flow
- But systems are siloed, actors are focused on:
 - AI researchers → technical protocols
 - Health systems actors → legacy infrastructures
 - Policymakers → sovereignty, ethics, consent
- Key Definitions:
 - Federated learning: Local training + shared model
 - Interoperability: Exchange + shared meaning of data
 - HL7 FHIR: Global standard for structuring + exchanging health data

AI in clinical trials exposes how fragile data systems become when information must move across borders and institutions.

Biobanks function as both physical and digital infrastructures, storing samples alongside metadata, imaging, and clinical information. They're crucial for clinical trials but raise big questions about ownership, consent, and cross-border sharing.

To integrate AI systems in biobanking research, there needs to be standardized metadata, shared ontologies, interoperable Electronic Health Records systems, and cross-border communication, which all exist in separate silos.

To further understand the misalignment between AI and biobank clinical trials and health systems more generally, three definitions are essential.

1. **AI Federated learning** lets models train across sites without moving raw data, creating a possible solution for data access to train machine learning AI systems.
2. Systems need to be able to talk to each other. **Ontologies** establish shared meaning, and interoperability means systems can exchange and interpret data consistently.
3. To talk to each other, there needs to be a language. We have a global language called **Health Level 7 (or HL7) Fast Healthcare Interoperability Resources (or FHIR)**. It's a global health data standard used in South Africa, Estonia, and Finland, but many low-resource systems lack the capacity to implement it.

Data Sovereignty, Biobanking & Cloud Constraints

Sovereignty barriers:

- Kenya: Tight genomic data export controls
- Uganda: Strict MTAs + benefit-sharing requirements
- Ghana: Increasing restrictions on sample/data export

Cloud fragmentation: Cloud systems operated by foreign companies → unclear jurisdiction

Impact on AI:

- Multi-agent systems require cross-site protocols + harmonized metadata
- Technical needs conflict with sovereignty + governance limits

This leads next to data sovereignty - the idea that countries control the data created within their borders. These rules often clash with AI's need for large, shared datasets and are complicated with digital biobanks using the cloud.

Data sovereignty in Africa is shaped by histories of extractive research.

- In Kenya, past misuse of malaria and HIV samples created long-term distrust, so Kenya now tightly restricts genomic data export and requires national approval.
- Uganda mandates detailed Material Transfer Agreements defining ownership and benefit-sharing before any samples can leave the country.
- Ghana's ethics committees increasingly require genomic data to stay within the country unless strict conditions are met.

Cloud systems scatter data across jurisdictions, and many centers are foreign-owned, undermining local authority and fueling extraterritorial control.

When AI is brought into the conversation, what is needed is stable communication protocols and harmonized metadata across many sites to be able to identify patterns in health data. But sovereignty rules in Kenya, consent constraints in Ghana, and cloud fragmentation in Nigeria collide with these technical requirements; in theory, **it can be concluded that AI models cannot be safely trained, validated, or deployed in multi-country clinical trials.**

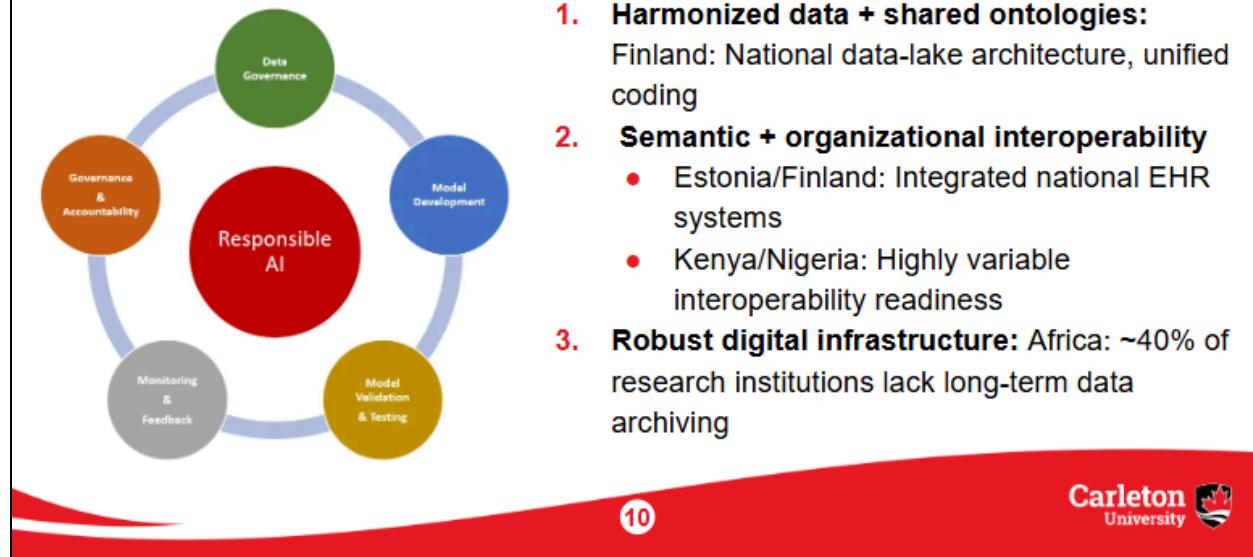
Case studies on Interoperability Failures

- **Semantic gaps:**
 - East African trial networks use different coding systems and metadata
 - AI models trained in Uganda cannot directly interpret Kenyan or Tanzanian data
- **Organizational gaps**
 - Fragmented governance, ethics, and consent frameworks
 - Paper-based or siloed digital systems block integration with global standards

Now looking at case studies, it is visible how interoperability challenges play out on the ground.

- **Semantic interoperability gaps** occur when hospitals and trial networks use different coding systems, diagnostic terms, and metadata structures. For example, in Uganda, Kenya, and Tanzania, trial networks rely on non-standard metadata. This means an AI model trained in Uganda cannot directly interpret data from Kenya or Tanzania without extensive re-mapping, which slows down research and undermines reliability.
- **Organizational interoperability gaps** arise when governance, ethics, and consent frameworks are fragmented, or when health systems remain paper-based and siloed. Rwanda illustrates this: while the national digital health strategy promotes interoperability, district hospitals still depend on legacy infrastructure, systems that cannot connect with FHIR-compliant platforms, so national ambitions remain disconnected from local realities.

Benchmarking: Conditions Needed for Responsible AI in Clinical Trials



AI models that respect sovereignty already exist, such as federated learning, and a global data standard, FHIR, that works in countries like Estonia and Finland. These examples show that AI can be integrated into health systems and clinical trials when foundations are strong.

The main barriers in the African context are infrastructure and technical capacity.

To align AI with global health priorities in biobank-supported clinical trials, three conditions are essential: harmonized data, interoperability across systems and governance, and robust digital infrastructure.

There is a pathway to success. The technical models and standards exist, and proof of concept is visible in countries with strong infrastructure. The challenge now is building capacity and systems so AI can reduce, rather than reproduce, global health inequities.

Theme 3: Policy Implications of AI, Data Silos & Adolescent Health

Focus of this section:

- How AI policy can better align with global health goals
- Diagnostic Lens: adolescent health in SSA
 - Mental health (MH) / (AMH)
 - Sexual & reproductive health (SRH) / (ASRH)
 - HIV prevention

Core claim

- Siloization makes AI incompatible with scaling needed to meet:
 - SDG 3 – Good Health & Wellbeing
 - SDG 5 – Gender Equality
 - SDG 10 – Reduced Inequalities

This final theme is policy measures needed to ensure that AI technologies can truly align with global health goals.

The analysis in this section focuses on adolescent health outcomes in SSA, specifically on mental health, SRH, and HIV prevention. The claim is made that data siloization makes AI incompatible with the scaling necessary to support global health goals related to adolescents such as SDG 3 (Good Health and Wellbeing), SDG 5 (Gender Equality), and SDG 10 (Reduced Inequalities).

Adolescents as a Key Demographic in Global Health

Adolescents are a key demographic to study as a diagnostic lens for evaluating AI alignment because:

1. Their health needs are intersecting, not siloed;
2. Their data is often fragmented, underreported, or collected within narrow mandates;
3. They are both the end users and future implementers of digital health tools; and
4. They embody demographic trends that will shape the region's development.

Adolescents in SSA face barriers that limit their opportunities to actively engage in the healthy behaviours that play a role in improving health outcomes that they can control (Musindo et al., 2023).

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The research is focused on adolescents rather than on youth because they are at a transitional phase in their lives where they are young enough to be susceptible to the social determinants of health (SDH) that they can't control, while becoming old enough to make decisions regarding health outcomes that are in their power to change.

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3. They are both the end users and future implementers of digital health tools; and
4. They embody demographic trends that will shape the region's development.

Despite this great promise in carrying on global health targets such as the SDGs, adolescents in SSA face barriers that limit their opportunities to actively engage in the healthy behaviours that play a role in improving health outcomes that they can control.

Siloization Umbrellas

VERTICAL

INSTITUTIONAL

ETHICAL

The three umbrellas of siloization that were identified in SSA adolescent health systems were **vertical silos**, **institutional silos**, and **ethical silos**.

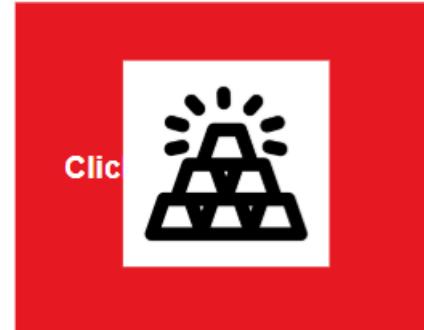
Vertical Silos

What are vertical silos?

- Typically short-term, specialized, *disease-specific programs* (e.g., HIV, maternal health)
- Designed with strong focus, clear accountability and rapid mobilization in a single area (Barrier, 2024)

How can they contribute to siloization?

- Fragmented service delivery
- Duplication of efforts
- Competition for limited resources
- Overfunding in some services, under-resourcing in others (Barrier, 2024)



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Vertical Silos emerge when health interventions are designed as short-term, vertical programs with narrow, disease-specific objectives. Vertical programs have played a major role in global health financing over the last two decades, as they produce measurable gains in areas such as HIV or maternal health.

The drawbacks of vertical programs are that they often operate independently of broader health systems, resulting in:

- fragmented service delivery,
- duplication of efforts,
- competition for limited resources, and
- overfunded services in some areas and under-resourced services in others.

Institutional Silos

What are institutional silos?

- Fragmented mandates and systems across **health, education, NGOs, community & digital actors**

Each operates with different

- data standards
- reporting systems
- ethical frameworks

Why is this relevant for AI innovation?

- AI is trained on institution-specific data, not shared systems
- Tools can't support integrated adolescent services
- Risk of incompatible datasets and blind spots
- Excludes culturally relevant perspectives that sit outside formal systems

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Institutional silos refer to **fragmented mandates, incompatible technologies, and inconsistent standards** among organizations involved in adolescent health.

Health ministries, education systems, community organizations, NGOs, and digital health actors frequently operate with:

- different data standards,
- different reporting system and
- different ethical frameworks, and

When AI tools are built on institution-specific data - rather than harmonized, interoperable systems - they are less likely to support integrated adolescent health services or reflect cross-cutting social determinants. This fragmentation even has the potential to inform incompatible datasets and exclude culturally relevant perspectives that function beyond formalized systems.

Ethical Silos

What are ethical silos?

- Research, privacy, and consent practices **that are inconsistent, adult-centered, or missing**
- Especially harmful in SSA where adolescents face:
 - Stigma and cultural/religious taboos around SRH
 - Risks of social exclusion or violence after disclosure

Why does this matter for AI?

When AI is trained on poorly safeguarded data, it can:

- Reinforce stigma and inequities
- Produce exclusionary outputs
- Undermine trust in digital health tools
- Deter adolescents from seeking care



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Ethical silos emerge when research practices, privacy safeguards, and consent processes are **either inconsistent, adult-centered, or absent**. Adolescents in SSA face vulnerabilities such as stigma and social exclusion or violence following disclosure.

When AI systems are trained on data collected without appropriate safeguards, they risk:

- reinforcing stigma and inequities,
- generating exclusionary outputs,
- undermining trust in digital health tools

Thus, altogether deterring adolescents from seeking care.

Why a Cross-Sectoral Framework Is Essential

Limits of siloed AI tools:

AI tools built inside narrow program mandates struggle to:

- **Capture interactions** across mental health, HIV, SRHR, education, etc.
- **Generate holistic insights** on adolescents' lives
- **Produce equitable outcomes** across groups and contexts

A cross-sectoral framework grounded in youth engagement, integrated indicators, and institutional collaboration essential for aligning AI with global health goals.

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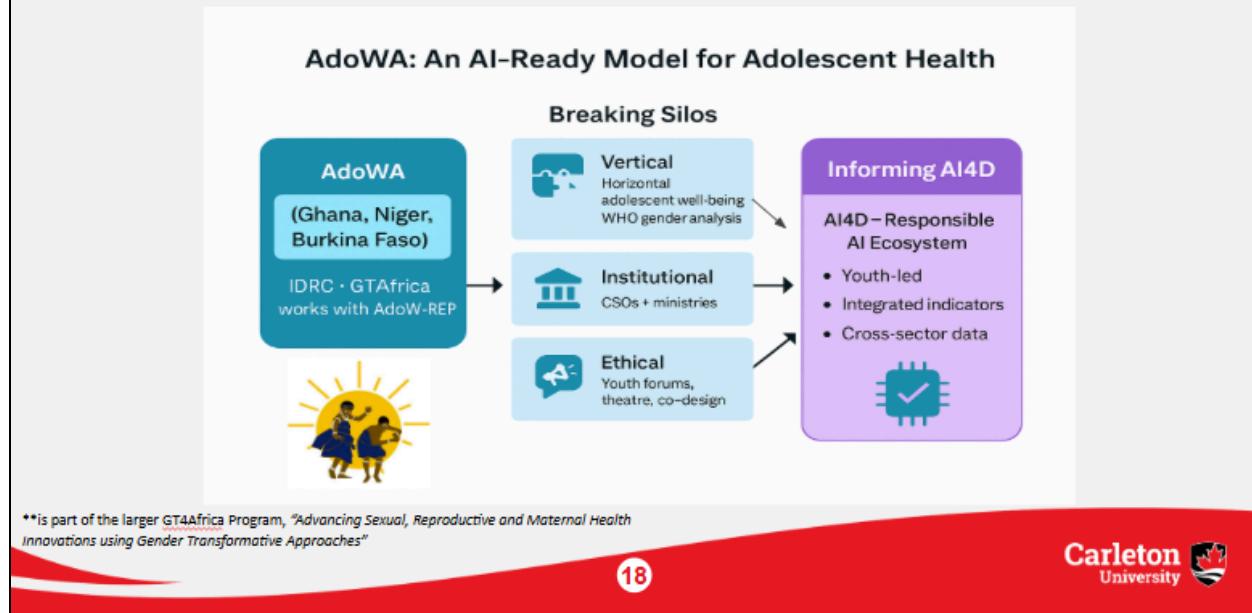
AMH, ASRH, and A-HIV prevention are mutually reinforcing. Poverty, gender norms, limited access to education and exposure to conflict and violence are just a few of the indicators that cut across all three health areas.

AI tools developed within siloed program mandates struggle to:

- capture these interactions,
- generate holistic insights, or
- produce equitable outcomes.

A cross-sectoral framework grounded in youth engagement, integrated indicators, and institutional collaboration is essential for aligning AI with global health goals.

IDRC's AdoWA Program: Breaking Silos in Adolescent Health



The AdoWA program shows that IDRC is already moving in the right direction to support youth health priorities in SSA. Over the course of AdoWA's implementation from 1 December 2021 to 31 August 2025, all 3 of the silos which I have been presenting on were strategically mitigated.

- **Vertical silos** are addressed by focusing on horizontal themes (like adolescent well-being) instead of limiting projects to single, specific, narrow health issues. AdoWA also uses global health frameworks such as WHO's intersectional gender analysis to make sure interventions reflect the real, intersecting challenges young people face.
- **Institutional silos** are reduced through cross-sectoral collaboration between CSOs and government ministries in health, education, and gender.
- **Ethical silos** are tackled through meaningful youth participation, including adolescent forums and theatre-based activities, which ensure that young people help design, shape, and evaluate the interventions that affect them.

These successes suggest that IDRC already has a strong foundation for scaling projects that can advance global health goals. The key question, then, is how lessons from AdoWA can inform IDRC's future investment decisions for AI-focused initiatives, especially under the AI4D-FCDO (Artificial Intelligence for Development Africa) partnership. Future AI pilots in adolescent health will benefit from incorporating frameworks with meaningful youth participation, intersectional indicators and cross-sectoral allyship.

Challenges, Needs and Opportunities

Challenge	Need	IDRC Opportunity
Brain drain, weak local technical capacity, limited inclusion in AI development	Building capacity and trust Long-term capacity-building + inclusive governance (career pathways, youth advisory boards, participatory processes)	Support multi-year fellowships, training hubs, and require participatory governance in AI4D projects.
Fragmented data systems, incompatible standards, weak cross-border research infrastructure	Technical harmonization Invest in interoperable architectures (FHIR adoption, harmonized ontologies, federated learning)	AI4D can fund regional interoperability pilots and standardization hubs.
Vertical programming, institutional fragmentation, historical distrust, sovereignty constraints	Programmatic harmonization Integrated indicators + transparent and balanced data stewardship across sectors	Fund federated data governance models & initiatives that focus on harmonizing across-sectors.

Taken together, this project's findings reveal a connected story: AI is not necessarily failing to connect with global health just because of technical limits, but also because it enters health systems that may be structurally fragmented, technically incompatible, and programmatically siloed.

- At the **structural** level, Theme 1 explored how funding asymmetries, academia-to-industry brain drain, and uneven data ecosystems separate AI developers from public health institutions and the communities they aim to serve.
 - **Opportunity for IDRC:** If not already being pursued - support multi-year fellowships, training hubs, and require participatory governance in AI4D projects.
- Theme 2 then demonstrated how these structural gaps translate into **technical barriers**. Even when there is willingness to use AI, it cannot operate effectively in multi-country research environments if sovereignty rules, incompatible metadata, paper-based records, and fragmented infrastructure clash with AI's technical requirements.
 - **Opportunity for IDRC:** Fund programs that build towards regional interoperability and standardization. An example could be funding practical, small scale projects where research centers or hospitals test adopting FHIR.
- Finally, at the **programmatic and population** level, Theme 3 explored how vertical programs, institutional fragmentation, and ethical silos limit AI's relevance for adolescent mental health, SRHR, and HIV services.
 - **Opportunity for IDRC:** Fund federated data governance models & initiatives that focus on harmonizing across-sectors.

Together, there are three interconnected needs: **building capacity and trust**; **pursuing technical harmonization**, and **programmatic harmonization**.

Thank You



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AI-Use Disclosure

This presentation utilised AI (ChatGPT-5) in the following ways:

- **Suggestions on cohesion:** Provided suggestions on how the different individual research questions and findings could be combined together for a singular cohesive flow.
- **Suggestions on combining recommendations:** Provided suggestions on how to collapse our multiple individual recommendations into a three common ones.
- **Editing support:** Reviewed speaking notes for grammar, clarity, and consistency in formatting and transitions.

All substantive research, evidence gathering, and analysis was done independently by each group member.