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Foundations & Futures:

Reimagining Public Health in the Artificial Intelligence Era Version 2.0

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Executive Summary

Artificial intelligence (AI) is reshaping what public health systems can see, understand and do. Across the Global South, countries are experimenting with how AI can help governments detect trends and risks earlier, allocate resources more effectively, and extend the reach of care. Yet the findings of this report make clear that the true measure of AI's promise lies in the strength of the foundations beneath it: the data, governance and institutional practices that determine whether innovations endure.

Drawing on interviews with government leaders, implementers and experts across regions, alongside a rapid landscape scan of nearly 200 AI-related public health use cases and a cross-country foundational readiness scan covering 63 countries, this analysis reveals a consistent pattern: AI readiness is about system readiness. Countries with complete, interoperable and trusted data ecosystems are better positioned to scale AI responsibly. Those that rely on fragmented or donor-led platforms face recurring cycles of pilot fragmentation, dependency and uneven impact.

The use-case landscape demonstrates that AI applications in public health are already diverse and expanding. Across countries, five recurring functional domains emerged: AI-enhanced diagnostics and screening at scale; surveillance, pattern recognition and early warning; public communication and behavior change; frontline worker decision support and service delivery; and system intelligence, planning and administrative optimization. While these applications differ in visibility and complexity, they share a common requirement: digitized, interoperable, government-led data systems that anchor them in routine public health operations.

Across the readiness scan, policy momentum is emerging faster than systems. Roughly one-third of countries reviewed have adopted a national AI policy, and most reference health. Yet connectivity remains uneven, interoperability is partial in many settings, core health data are incomplete in a significant subset of countries, and digital health workforce capacity is thin. These structural gaps, not a lack of algorithms, are the binding constraints on AI adoption at scale.

Five dimensions emerged from the interviews as decisive for meaningful adoption:

- Governance and Institutional Ownership: Governments must lead, safeguarding data sovereignty, setting procurement terms, and aligning AI with national priorities.
- Data and Digital Systems: AI depends on integrated, high-quality, population-based data, not on isolated tools.
- Connectivity and Access: Reliable infrastructure determines who is visible to public health intelligence and who remains excluded.
- Human and Institutional Capacity: AI amplifies judgment; without digital literacy, analytic skill and oversight capacity, systems cannot function responsibly.
- Sustainable Financing: Long-term investment is needed to make sure the impact persists beyond project cycles and demonstration pilots.

To move beyond broad notions of "readiness," the report introduces a structured Use-Case Prerequisites Matrix. Rather than treating AI adoption as binary, the matrix distinguishes between minimum conditions required to initiate a use case safely, accelerators that improve performance and adoption, and scale-critical foundations necessary for sustained, systemwide institutionalization. This framing reinforces a central finding: AI cannot compensate for weak systems. It can only build on digitized workflows, interoperable registries, defined decision pathways, and accountable governance structures.

These findings elevate foundational public health data systems such as civil registration and vital statistics, surveillance systems, health information platforms, and facility and workforce registries, as the true enablers of AI. When government-led, population-based, continuous, interoperable, and sustainably financed, they transform AI from a novelty into a durable public good capable of improving assessment, detection, planning and service delivery.

The call to action is clear.

- Public health data strategies must be sustainable: Ensure financing and institutional capacity, not just for initial investments but also for continued maintenance, integration and oversight.
- Public health data structures must be government-owned and publicly governed: Institutionalize stewardship that protects sovereignty, strengthens procurement leverage, and builds public trust.
- Public health data systems must be comprehensive, inclusive and contextualized: Treat data and digital systems as national infrastructure at the service of the public interest, rather than framing them as stand-alone, temporary projects that risk deepening inequities.

The promise of AI will be most fully realized when it is integrated into countries' broader digital public infrastructure. Digital public infrastructure anchored in civil registration, digital identification, interoperable data exchange and secure consent frameworks provides the structural backbone on which AI can operate responsibly. Investing in this foundational ecosystem enables governments to layer AI tools in ways that improve efficiency, generate anticipatory intelligence and strengthen accountability rather than fragmenting authority or outsourcing control. As countries navigate the tension between the foundations and futures of AI in public health, the defining question is not how quickly AI can be deployed, but whether it is embedded in systems strong enough to sustain it. Getting the foundations right will determine whether AI deepens fragmentation and inequities or helps build durable public health intelligence that enables governments to act earlier, allocate more equitably, and protect populations more effectively over time.

Introduction

AI is defined by WHO and the U.S. Centers for Disease Control and Prevention (CDC), as a "machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments" and that learns from data over time.[1,2] In a public health context, these systems use methods such as machine learning and natural language processing to analyze large, diverse data sources and generate predictions, classifications or recommendations that support core public health functions, including disease surveillance, outbreak detection and modeling, health promotion, policy analysis, and resource planning. As described by WHO and the CDC, AI in public health should operate within ethically governed, equitable and accountable health systems, with explicit attention to data protection, bias, transparency and public oversight.[3]

AI is reshaping what public health systems can see and do. Around the world, new tools that link data across sectors and sources are showing how next-generation public health systems can strengthen detection, sharpen policy and planning, and change how governments engage with their communities.[4] [5] When data are connected and complete, AI can uncover previously hidden patterns, such as how diseases cluster, how climate and poverty influence health vulnerabilities, and how communities manage care. When tools are tailored to local contexts, they can help midwives, youth workers and district managers gain real-time insights on patient care in their own languages. When systems are interoperable, AI can help predict supply chain shortages, detect anomalies earlier, and close the gap between information and action.

The momentum is real: Countries are moving quickly to understand where AI can add value and are beginning to assess their readiness for AI technology in a more structured way.[6] Yet, as interest grows, so do the practical and operational challenges. The promise of AI lies not in the sophistication of its tools or in outputs achieved at the demonstration level, but in its ability to improve public health outcomes inclusively and at scale. A country's ability to realize this value will depend on the strength of the foundations on which AI relies: the data it uses, the governing institutions, and the people who use its outputs to make decisions.[7] Without these foundations, the speed of AI development risks overpassing the infrastructure needed to support effective deployment. This can lead to potentially devastating long-term consequences, including loss of data sovereignty, weakened people protections, widening health inequities, and temporary, expensive pilots.[8]

Across the Global South, tensions are evident: AI's potential is growing rapidly, but readiness varies. Fragmented data systems with limited interoperability, gaps in digital and analytic capacity, and a lack of governance frameworks all prevent AI tools from scaling in ways that are reliable, trusted, and sustainable.[9] As a result, pilots proliferate without integration, investments cannot be built upon and leveraged, and systems produce more noise than actionable intelligence.[4]

The focus ahead should not just be on creating more tools, but also on building foundational public health data systems connected to national digital public infrastructure, creating an enabling environment for intelligent systems that work for, not against, **the public's health.** Strong data pipelines, interoperable platforms, connected datasets, and digitally enabled workforces can make AI a public health impact multiplier, helping governments shift from reacting to crises to anticipating them, and turning scattered information into meaningful insights. This is the focus of this landscape exercise: understanding how "readiness" is experienced and understood, and what conditions must be in place to ensure that AI is used in the service of public health objectives rather than as simply a "shiny new object." Defining the foundational requirements for safe, equitable and effective integration of AI in public health will be a determining factor in whether AI strengthens public health practice or adds new layers of fragmentation, disparity and unrealized promise.

About This Report

This report is based on three inputs: 1) Semi-structured interviews with representatives of ministries of health across Africa, the Middle East and South America, as well as with funders, implementers, regional experts and global thought leaders; 2) A rapid landscape scan of AI-related public health use cases across Africa; and 3) A country "readiness" scan that compiles fundamental indicators on AI policy, connectivity, data and workforce. The report progresses from foundational concepts to practical applications. The Foundations and Futures section summarizes the interview findings, explaining the core components of government-led, population-scale data systems and the AI applications they enable. **Four Spotlights—Rio de Janeiro, Recife, Rwanda and India**—illustrate how these ideas are applied in real-world settings. The Public Health Systems AI Readiness in the Global South scan adapts these themes into five readiness dimensions—governance, data and digital infrastructure, connectivity, human capacity, and funding.

The Discussion section introduces foundational public health data systems, highlights six characteristics that make them well suited for AI, and issues a **call to action** outlining implications for governments, funders and implementers.

About Version 2.0

This version of the report represents an incremental update to the original analysis, incorporating targeted refinements based on external feedback, a facilitated convening at the Global Digital Health Forum, and follow-up consultations with senior public health experts. These inputs prompted selective adjustments to the use case framing and prerequisites matrix, including clearer alignment between use cases, system conditions and pathways to scale. Version 2.0 also incorporates initial country-specific insights from ongoing engagement with senior government, implementation and technical leaders in India, undertaken in the context of India's evolving health AI strategy and global convening agenda. These discussions reinforced the core system-readiness framing while revealing additional operational and governance considerations relevant to large-scale public systems. This iteration is intended for release at the Global AI Summit in India in February 2026. Further country-level consultations are planned ahead of a final version, expected in the third quarter of 2026, to deepen and validate cross-context insights while preserving the report's core analytical structure.

The Appendices include:

- **Appendix 1. Foundations and Futures: Thematic Interview Analysis**
  Summarizes cross-country stakeholder interviews in structured tables, highlighting current state, insights, and recommendations, as well as governance and legal considerations for AI in public health.
- **Appendix 2. Foundational AI Readiness by Country**
  Provides a country-by-country snapshot of AI readiness using publicly available indicators of AI policy, connectivity, interoperability, health data availability, and health and digital health workforce capacity.
- **Appendix 3. Rapid Use-Case Landscape Scan (Africa+)**
  Presents a desk-based scan of AI applications for public health in African countries plus selected comparators, grouped into major functional use-case categories, as well as India specific examples.
- **Appendix 4. Tiered Prerequisites for AI Use Cases in Public Health**
  Presents the AI Use-Case Prerequisites Matrix developed as part of this consultation process. The matrix organizes key public health AI use cases alongside the system conditions required for their safe initiation, strengthened performance, and sustained scale.

Foundations and Futures of AI in Public Health

Findings and Insights

Stakeholder Interviews and Thematic Analysis

We conducted semi-structured interviews with representatives of ministries of health across Africa, the Middle East and South America, as well as with funders, implementers, regional experts and global thought leaders. We applied a framework-based thematic analysis, organizing insights under two overarching themes: Foundations for Artificial Intelligence in Public Health and Futures for Artificial Intelligence in Public Health. Within this structure, we examined six interconnected analytic domains: Critical Building Blocks, Promising Use Cases, Gaps and Needs, Concerns and Risks, Enablers and Drivers, and Governance and Legal Considerations. These domains were defined through a landscape review and Vital Strategies' previous experience supporting public health data and digital systems. All participant reflections were coded into this framework to enable structured comparison across countries, regions and stakeholder groups. We focused on recurrent patterns, highlighting insights only when they were independently raised by multiple participants across different contexts, rather than relying on a single viewpoint.

Table 1: Synopsis of Preliminary Thematic Analysis of Interviews (see Appendix 1 for full tables of summarized analysis)

Theme	Subtheme	Summary
Critical Building Blocks	**Foundational Data Systems & Interoperability**	Data systems remain fragmented, incomplete and siloed, without unique IDs or interoperability; weak civil registration and vital statistics (CRVS) and inconsistent digital infrastructure limit AI's reliability and reach. Countries lacking core registries, facility lists, and national standards struggle to scale AI. Where long-term public data infrastructure exists, digital adoption is far more effective.
	Governance, Legal & Policy Frameworks	Most government digital strategies do not address AI, and data protection enforcement is weak. Clear rules for data access, consent and AI oversight are missing but essential.
	Institutional Ownership & Coordination	Coordination is weak, leading to fragmented pilots and unclear national leadership. AI efforts often start with tools instead of problems. Stronger priority-setting is needed.
	Digital Public Infrastructure	Foundational registries (ID, CRVS, facility lists, workforce registries) are required infrastructure for AI to work. Countries with these systems in place absorbed digital tools more effectively during COVID.
	Human Capacity, Digital Literacy & Inclusion	Digital literacy and AI/ML (machine learning) expertise remain low among health care workers, with many relying on paper systems. Differences in access, language and digital behavior show that populations are unevenly prepared to use AI tools.

Theme	Subtheme	Summary
Promising Use Cases	**Predictive Analytics & Early Warning Systems**	Predictive models enhance the detection of outbreaks, missed health care visits and emerging risks. They enable more proactive public health planning when linked to multisectoral data.
	Diagnostic Imaging Support	AI can triage TB, cancer, COVID and X-ray images, easing specialist workloads and speeding diagnosis. This was one of the most consistently high-impact use cases identified.
	Hybrid Human–AI Support for Frontline Workers	AI augments clinicians' and community health workers' (CHWs) capacity through decision support and risk-flagging tools. Human judgment remains essential for final decisions.
	Behavior Change, Personalization & User-Facing Chatbots	Chatbots tailored to local languages and cultures improve engagement, especially among youth and low-literacy groups. AI enables personalized and scalable communication.
	Cross-Sector Intelligence for Public Planning	Integrating health, education and social data helps identify at-risk groups and improves targeted service delivery. Supports more equitable public planning.
Concerns & Risks	**Data Protection, Ethical Risks & Sovereignty Threats**	Countries worry about data leakage, commercial misuse, sensitive information exposure, and loss of control over data hosted by external vendors. Weak consent systems and unsafe handling of youth, sexual and reproductive health (SRH), and refugee data heighten ethical risks, while vendor-controlled infrastructures threaten national sovereignty.
	Data Fragmentation, Poor Quality & Algorithmic Bias	Fragmented, incomplete or nonrepresentative datasets undermine AI performance and produce biased outputs. Models trained outside local contexts routinely misfire, reinforcing inequities and excluding underserved groups.
	Sustainability, Cost & "Pilotitis"	Many AI solutions collapse after pilot funding ends due to high maintenance and computing costs. Without long-term domestic financing or integration into national systems, tools remain fragmented experiments rather than scalable solutions.
	Workforce Readiness, Trust & Weak Oversight Capacity	Low digital literacy, fear of job loss, and limited understanding of AI reduce workforce trust. At the same time, governments lack the oversight, audit systems and regulatory capacity needed to evaluate or monitor AI tools, allowing opaque "black box" systems to operate without accountability.
Enablers & Drivers	**Foundational Digital & Computing Infrastructure**	Reliable power, data centers, broadband and cloud infrastructure underpin scalable AI. Countries that invest in shared platforms rather than vertical systems move faster and achieve greater sustainability.
	Policies, Laws & National AI Strategies	Clear national AI/digital strategies guide responsible adoption, protect citizens, and align partners. Countries want flexible frameworks that are rooted in ethics and technical rigor.
	Integration into National Systems & Sustainable Financing	AI becomes durable only when embedded in national health information systems and supported through domestic budgets. Long-term financing for maintenance, integration and demand creation is essential.

Theme	Subtheme	Summary
	Regional Collaboration, Partnerships & Embedded Talent	South–South collaboration, peer networks and embedded technical talent help countries negotiate better, build capacity and scale AI more effectively. Codesign and human-in-the-loop approaches strengthen the sense of local ownership.
	Trust, Culture, Language & Public Data Governance	Adoption grows when tools reflect local languages, cultural norms and youth digital habits. Public data governance and data-justice approaches ensure that governments and communities retain control over value and decision-making.

Additional Country-Specific Insights

India

In India, the findings largely reinforced the relevance of the framework presented above and in Tables 1a–1c (see Appendix 1), while also highlighting system dynamics not yet fully reflected. Digital and AI systems introduce greater clarity and accountability in health care, providing visibility into system performance that enables targeted, data-driven improvement. As manual processes shift toward digitized dashboards, administrators gain a clearer view of service gaps, resource allocation patterns and operational bottlenecks. At the same time, increased transparency can provide an early window into potential conflicts of interest, procurement distortions or incentive misalignment as digital foundations mature, allowing governance risks to be identified sooner rather than after harm occurs. India's approach to data readiness is evolving toward high-quality, operational utility. The focus has moved beyond data volume or completeness to ensure that information reflects real-world conditions across diverse devices and care settings, thereby strengthening clinical relevance and system reliability. Participants emphasized that state-level pilots scale only when aligned early with national platforms and noted limited investment in AI for prevention, behavior change, and mental health despite those areas' potential for systemwide impact. From a governance perspective, bureaucratic continuity provides a stable foundation for long-term digital transformation, helping projects endure beyond political cycles, while policy rigidity was identified as a constraint on adoption. Leaders also stressed the importance of anticipatory governance, with risks such as connectivity gaps and vendor dependence identified and tracked from the outset.

Foundations: Critical Building Blocks to Capture the Promise of AI for Public Health

Across the Global South, governments, researchers and partners are exploring how AI can strengthen disease surveillance, improve planning and extend the reach of public health programs. The momentum is undeniable. At the same time, every conversation with ministries and experts pointed to a standard warning:

> ***"AI moves faster than the systems meant to support it."***

When data is incomplete, unconnected or poorly governed, even the most sophisticated models struggle to deliver value. Participants across countries described readiness not as a single benchmark but as a set of conditions that determine whether AI becomes a practical tool or an expensive experiment.

Governance and Institutional Ownership

Government representatives emphasized that readiness is ultimately about trust, sovereignty and control. Policies alone are insufficient; countries must be able to operationalize and enforce them in order to ensure that **AI systems are accountable to the public interest.**

"If countries don't have the technical and political foundations for robust governance, coherent policies and trusted infrastructure, technologies won't scale, and the enabling environment won't be pressure-tested." —Global Health Leader

Respondents repeatedly warned of the risks of dependency, especially when external partners control infrastructure, data pipelines or computing environments. One implementer put it bluntly:

"Who owns that data after the solution is built or after the partnership ends? If we come back to ask for the information, we're either charged a fee, or it sits in a system that cannot integrate with our platforms. These are the risks … data sovereignty and ownership must be protected."

Respondents were consistent: ***Countries cannot govern what they do not control, and the architecture is where that control lives.*** They highlighted that owning servers, cloud rules, identifiers, governance structures and procurement terms enables ministries to align AI tools with national priorities, prevent vendor lock-in and ensure accountability. One respondent, when discussing the sovereignty of language models and how they are built, said, *"Is there a space for smaller language models that are much more informed by a particular context for that context, as opposed to this constant obsession with large language models?"* This point reinforces a broader theme across interviews: Readiness is not only about having data—it's also about designing, developing and owning the models that interpret it.

Data and Digital Systems

Throughout our conversations, respondents emphasized that AI readiness is not just about hardware or platforms. **Readiness starts with the "digital backbone."** Ministry of Health officials, implementers and global experts also all emphasized that before any digital system can apply AI responsibly, **its data must be complete, of reliable quality, and interoperable across programs and institutions**.

"Data quality, interoperability, and repositories have been identified as the absolute priority and the main obstacles to overcome to enable effective AI adoption." —Ministry of Health Representative

In this context, a global thought leader emphasized the need for a digital public infrastructure (DPI) mindset, noting that *"AI needs DPI thinking … building foundational digital building blocks at a country level, ID systems, payment, data exchange, and doing that in a way that they can interoperate with other pieces and you can build on top of them."*

A multinational implementer stressed that these foundations are what make for an intelligent public health system.

"Everyone wants to fund the shiny thing, the new app, the chatbot, the pilot, but not the systems that make those things work. The real investment needs to go into the groundwork: data quality, governance, infrastructure, and people. Without that, everything else is temporary."

Alongside infrastructure, several experts argued that readiness also requires a shift from "bright, shiny" technology adoption to problem-driven inquiry: understanding pain points, clarifying the outcomes sought, and identifying the complete data requirements for each use case.

As one regional thought leader put it, *"Sometimes it's data for data. We need to be explicit about the outcome we're trying to achieve and then pull the data that way."*

One respondent also explained that the real risk is not only missing foundational public health data but also neglecting additional useful data sources: *"We often conclude there is 'no data,' not because the data is absent, but because we have looked only in traditional locations, official registries, surveys, or external databases, and overlooked the data that is generated continuously by people, sectors, and systems outside formal boundaries."*

Aligned with a broader concern echoed across various settings—that incomplete records, inconsistent formats, duplication and siloed information are significant problems—this leader argued that accurate data and digital system readiness require interrogating the mental models that define what governments believe "counts" as data in the first place. Are countries missing an opportunity to integrate relevant data that already circulates within telecom systems, informal-sector networks, urban mobility patterns, environmental sensors, citizen-reporting apps, and routine administrative processes?

Connectivity and Access

Described as both a technical and an equity issue, broad-based digital connectivity is identified as core to foundational public health systems. Experts stressed that even well-designed digital systems remain disconnected when frontline facilities cannot reliably upload or receive data.

“The readiness question is: Is there an enabling environment in terms of simple things like connectivity and in-country cloud hosting?” —Implementer

In many regions, limited broadband coverage, power fluctuations and unstable online access restrict who can participate in digital transformation and who remains excluded. Expanding mobile reach to rural and underserved areas allows frontline workers to access and transmit information in real time, linking community-level data to national systems.

Respondents also raised structural constraints that limit the ability to build large data repositories to power AI systems. A regional thought leader highlighted the cloud and storage challenge: *“AI requires huge amounts of data. So, what does that mean for storage? Data storage facilities are expensive and require constant electricity.”*

From a health equity perspective, connectivity is a matter not only of technical readiness, but also of who becomes visible to public health intelligence. When connectivity gaps mirror existing patterns of marginalization (for example, affecting rural communities, informal settlements, nomadic populations, people with disabilities and linguistically diverse groups), AI systems risk reinforcing inequities by learning primarily from the data of those already connected. Respondents emphasized that equitable AI requires equitable infrastructure: Without intentional investment in inclusive connectivity, populations with the greatest health burdens may remain underrepresented in data systems and less likely to benefit from intelligent services. Ensuring that connectivity reaches all communities is therefore a foundational step toward AI adoption that strengthens, not stratifies, public health outcomes.

Human and Institutional Capacity

Participants consistently returned to a simple truth: **AI readiness is human readiness.**

Across all regions, respondents reiterated that AI only reflects the level of intelligence it is built on and the discernment that governs it. Ministries and implementers stressed that without the human capabilities necessary to question, interpret, validate and govern AI outputs, the tools themselves would be of limited value.

“Artificial intelligence solutions thrive when humans are ready to use it, question it and improve it. But more critically, AI does not create intelligence. It amplifies the level of human judgment on which it builds. So, when people stop thinking critically, machines stop being intelligent.”
—Global Health Leader

Governments emphasized that readiness is not only about having AI engineers or data scientists at the Ministry of Health, but also about the everyday competencies and capabilities required to make systems function. These include digital literacy, statistics, data engineering, system maintenance and the ability to interpret outputs in context.

A ministry representative illustrated the challenge: *"There's limited AI technical expertise in health care… even the health workforce is still being exposed to digital literacy. Some people still say, 'Please give me my pen and paper.' If that person is doing that, then how are we getting them to understand how AI works and how it would help?"*

Several participants noted that **as automation expands, human-led processes become even more essential**. They highlighted functions such as decision-making, data validation, contextualization and ethical oversight as critical to continued human oversight. Respondents emphasized that AI is not a replacement for critical judgment or for state capacity. Instead, its value will depend on whether countries cultivate the institutional muscle to interrogate the outputs, maintain the systems responsibly and sustain a workforce that can adapt as technologies evolve.

Financing and Sustainability

Finally, participants stressed that **readiness requires stable, long-term financing that treats data systems as digital public infrastructure rather than innovations or temporary projects.** Donor-funded pilots often demonstrate value, but many stall before systemic deployment or scale because ministries lack the resources to maintain, integrate or expand them across pre-existing public health systems.

One implementer highlighted the challenge: *"The technology is the easy part … the hardest part is not the tech build, it's the scaling part, the sustaining part, the institutionalization of the program. These things are expensive and resource-intensive. People are happy to pay for a piece of tech, not happy to pay for the implementation."*

This point echoed across conversations: Too much money goes to prototypes and too little to the infrastructure, workforce, and operating budgets needed to keep them going.

As a global thought leader asked: *"Are you going to say you'll pay for vaccines but not how to get vaccines into arms? That's what's happening with digital tools: Funders pay for the tech and expect miracles."* Costed strategic planning for sustained investment is the difference between proof of concept and public value. Without financing models that fund the "unglamorous" foundations of hosting, connectivity, maintenance, integration and training, countries risk becoming trapped in cycles of pilots that never scale.

Foundational AI Readiness for African Public Health Scan

This scan provides a high-level overview of how African countries, alongside selected comparator countries (India, Indonesia, Sri Lanka, Bangladesh, Thailand, Jordan, Brazil and Paraguay), are positioned to adopt AI in public health. It is based on desk review of publicly available sources and has not been validated with governments. Findings should therefore be interpreted as indicative rather than definitive, as they may not reflect recent reforms or subnational variation. The detailed country-level results are presented in Appendix 2.

The scan draws on five domains: AI policy (presence and status of national strategies), connectivity (ITU ICT Development Index), interoperability (Global Digital Health Monitor score), health data availability (WHO SCORE 2023), and workforce capacity (clinical workforce density and digital health workforce maturity). Together these domains provide a directional picture of foundational conditions rather than a measure of AI performance or implementation maturity.

Results

Across the region, foundational readiness for AI is uneven, with clear pockets of progress alongside structural gaps.

- **Policy:** Approximately 35% of countries (22) have an adopted national AI policy, with another 26% (18) in draft or pending stages. Roughly 40% have no identifiable AI policy. Among adopted strategies, most explicitly reference health, suggesting growing recognition of AI's relevance to public health. However, the presence of a policy does not necessarily indicate implementation capacity or sustained financing.
- **Connectivity:** The average ICT Development Index score is approximately 60, indicating moderate digital infrastructure overall. Around 38% of countries score 70 or higher, reflecting relatively strong digital access and mobile penetration. In contrast, about 15% score below 40, where limited connectivity may constrain cloud-based tools, real-time data exchange and digital service delivery.
- **Interoperability:** Of 47 countries with available data, just over half (about 54%) score at level 3 or higher, suggesting moderate integration across digital health systems. Only a small number reach the highest levels, indicating that full data exchange across platforms remains limited in many settings and may restrict more advanced AI applications.
- **Health Data:** The average availability of SDG health data is roughly 63%. About one-third of countries exceed 70% availability, reflecting relatively strong reporting of mortality, service coverage and risk factor indicators. However, roughly one in six falls below 50%, pointing to significant gaps in core health statistics that may limit the reliability of population-level analytics.
- **Workforce:** Health workforce density remains low across most countries, with only 15% to 20% showing staffing levels that suggest relatively stronger clinical capacity. Digital health workforce maturity is thinner still, with only about one-third reporting more advanced digital health teams. This indicates that even where policy and infrastructure exist, technical and operational capacity may constrain sustained AI adoption.

Taken together, the scan suggests that while policy momentum is emerging, the binding constraints in many settings lie in connectivity gaps, partial system integration, data completeness and workforce depth. These patterns reinforce the importance of sustained, government-led investment in foundational digital and data systems before large-scale AI can be deployed.

Futures: What Intelligent Public Health Systems Can See and Do

With the right foundations in place, data systems and AI can help public health practitioners see, learn, and act more quickly and effectively. The same infrastructure used to record an illness can help predict it. In prepared systems, intelligence appears as anticipatory insight. Linked, high-quality data allow models to move beyond describing yesterday's caseloads to identifying tomorrow's risks.[10] **Predictive analytics and early warning** consistently emerge as the strongest near-term AI opportunity, with models already used to detect outbreaks, issue early alerts and anticipate where services or supplies will be under strain.[11] These systems draw on diverse data streams, including routine health records, environmental and climate indicators, satellite imagery, wastewater signals and open-source reports to detect anomalies before they escalate into full crises. They also support the early detection of social harm, for example, by surfacing patterns in patient narratives that suggest gender-based violence, mapping underserved areas that have persistently low vaccination coverage, or combining biometric trends and service-use data to identify populations at heightened risk of malnutrition.[12 13]

Enhanced public health intelligence is also reshaping how disease is detected and managed in everyday care, with clear equity implications.[14] **AI-enabled diagnostics** can read X-rays, slides, images and rapid test results at scale, extending specialist-level capacity to detect tuberculosis, malaria, cancer and other conditions into clinics, mobile units and hard-to-reach settings where radiologists and laboratory experts are scarce.[15] At the same time, global reviews warn that many diagnostic algorithms are trained primarily on data from high-income countries, with limited representation of populations in low- and middle-income settings, those with darker skin tones, children, and other underserved groups, leading to performance gaps and the risk of widening inequities.[16]

For individuals and communities, AI applications can support **how they receive information and navigate systems**.[17] Conversational tools can offer private, context-aware guidance on sexual and reproductive health (SRH), HIV prevention, maternal health, mental health and everyday self-care that provides engagement without stigma, discrimination or risk of violence.[18] These systems can operate in local languages, recognize spelling and slang, and adapt content to a person's age, gender or disability. Rather than generic mass messaging, individuals can receive tailored prompts, reminders and reassurance at the right moment, through channels they already use. Behavior change becomes less about broadcasting and more about continuous, two-way support that is rooted in trusted digital identities and protected data. For frontline workers, public health intelligence appears as **embedded, practical support**.[19] When data systems are interoperable and up to date, AI can sit alongside community health workers, nurses and primary care providers as a quiet second pair of eyes: organizing protocols, structuring triage questions, suggesting next steps and highlighting when a case needs referral.[20] It can handle administrative tasks such as cleaning and coding records, reconciling duplicates, routing questions and generating summaries, so that limited human time is spent on judgment and care rather than on paperwork.

In primary care systems, which often struggle with continuity, these tools help maintain **disease registries** and track patients across community and facility encounters, reinforcing adherence to best practices and monitoring of clinical outcomes.

At the systems level, intelligence becomes **the means by which governments see and steer the health system as a whole**. AI models built on reliable administrative, geospatial and service data can forecast commodity demand, optimize supply routes and identify facilities at risk of stockouts before they occur. They can map which neighborhoods, schools or districts are consistently underserved and simulate how shifting staff, budgets or services would change access. When health data is securely linked to social protection, education and demographic information, planners can identify families and communities who are most likely to fall through the cracks and design more precise, equitable responses.

Rapid Use-Case Landscape Scan

Searches were carried out by subregion and then by country, treating each country as a case. For each we identified AI tools, digital health projects, pilots or research related to public-health functions. Identified examples were followed up to clarify purpose, context and implementation status, and to locate related initiatives where possible. This process yielded 277 entries, which were coded by AI technology type, public health relevance, use case focus, verification status, and activity status (active, pilot or research/prototype). After excluding entries without a public-health function, 198 examples remained. A qualitative synthesis of these examples identified five recurring functional themes, which structure the use-case findings:

1. **AI-enhanced diagnostics and screening at scale**
2. **AI for surveillance and early warning**
3. **AI for public communication and behavior change**
4. **AI for frontline worker support and service delivery**
5. **AI for system intelligence, planning and resource allocation**

Descriptions and illustrative examples for each theme are provided in Appendix 3, Rapid Use-Case Landscape Scan (Africa+)

Through post-launch consultations and follow-up discussions, the initial use-case framing was refined and clarified to better reflect how AI is applied in practice and how system prerequisites vary across domains. These refinements do not replace the original landscape scan but sharpen the alignment among use-case categories, real-world implementation pathways and the prerequisite matrix. The updated use case categories reflected in the matrix are described below:

1. AI-Enhanced Diagnostics and Screening at Scale *(e.g., TB, cancer, COVID, CT/X-ray)* refers to the use of machine learning, computer vision and related methods to analyze clinical images, signals, laboratory outputs or screening data, enabling earlier and more accurate disease detection. These systems are typically embedded in digitized diagnostic workflows and serve as decision-support tools rather than autonomous decision-makers. At scale, their effectiveness depends on digitized imaging infrastructure, standardized acquisition protocols, locally representative training data, integration with clinical information systems, and clearly defined referral and treatment pathways. When properly governed and calibrated to local epidemiology, these tools can extend specialist-level screening capacity into primary care, mobile services, rural settings and resource-constrained environments, reducing diagnostic delays and supporting more equitable access to care.

2. AI for Surveillance, Pattern Recognition and Early Warning uses predictive analytics, anomaly detection, natural language processing, and multi-source data integration to identify emerging health threats, detect unusual patterns and anticipate population-level risks. These systems analyze routinely digitized surveillance, as well as clinical, environmental, mobility and laboratory data streams to strengthen public health intelligence. Beyond routine outbreak monitoring, these applications are central to pandemic preparedness and response. With interoperable data architecture and sustained routine reporting, they can detect early respiratory signals, zoonotic risks, excess mortality patterns, supply chain strain, and other indicators of systemic stress. Their value depends on clear linkage to response mechanisms, defined decision authority, and governance structures that maintain data quality, equity and public trust.

3. AI for Public Communication and Behavior Change uses generative AI, natural language processing and personalization algorithms to deliver targeted, culturally responsive health information and support behavior change at scale. These systems operate through digital communication channels, including SMS, messaging platforms, mobile applications and interactive voice systems. Rather than broadcasting generic messages, these tools enable segmentation, adaptive messaging and two-way interaction that supports prevention, adherence, risk awareness and service navigation. Their effectiveness depends on trusted digital channels, clear consent frameworks, localization to language and cultural context, integration with human support or referral systems, and public governance mechanisms that define boundaries for automated health advice and safeguard vulnerable populations.

4. AI for Frontline Worker Support and Service Delivery refers to decision-support algorithms, triage systems, workflow assistants and knowledge tools embedded in digitized care environments to augment the capacity of community health workers, nurses and clinicians. These applications structure clinical decision pathways, flag high-risk cases, automate documentation and improve referral coordination across levels of care. These tools work best when core service-delivery processes are digitized and interoperable. Defining roles clearly, where AI supports, and humans make decisions, along with escalation protocols, supervision, and workforce training, is crucial for safety, accountability, and ongoing use. When integrated effectively, these systems can enhance continuity of care, lessen the administrative workload and improve quality throughout distributed primary health systems.

5. System Intelligence, Planning and Resource Allocation uses AI on datasets related to administration, epidemiology, geospatial information and service delivery. This generates population-level insights to guide policy decisions, budgeting, logistics and strategic planning. These systems go beyond managing individual cases, enabling governments to view and direct the entire health system effectively. Their functionality relies on interoperable digital systems, legal frameworks for cross-sector data sharing, transparent analytical results and institutional capacity to turn insights into funded actions. When based on high-quality, population-level data, these tools can predict commodity demand, identify service gaps, simulate policy scenarios and help ensure more equitable resource distribution. This category includes two system-critical subdomains:

5a. Data Quality Automation and Population-Level Analytics uses AI to clean, structure, classify, deduplicate and harmonize large administrative and registry datasets. These applications strengthen the reliability and usability of data pipelines that support surveillance, planning and service delivery. By automating coding, resolving inconsistencies and generating standardized outputs, these mechanisms improve data completeness, comparability and timeliness. They are often less visible to end users but are foundational to accurate forecasting, evaluation and cross-system intelligence.

5b. Administrative and Workflow Optimization uses AI to streamline high-volume, rule-based processes in health systems, including scheduling, documentation, claims review, routing inquiries, supply logistics and other operational tasks. These applications reduce manual workload, improve processing speed and create structured digital records that feed downstream analytics. Their effectiveness depends on workflow redesign alongside automation, integration with existing platforms, change management and governance mechanisms that ensure efficiency gains translate into service improvement rather than displacement or opacity.

See Appendix 3, Rapid Use-Case Landscape Scan (Africa+), for more examples.

Spotlights

As countries expand their digital health information infrastructure, new opportunities emerge to use routine data at both the individual and community levels to strengthen health surveillance and support earlier action to prevent harm. At the individual level, clinical information can provide risk signals that guide clinicians to further investigation and intervention. Complementing this is early detection at the population level, i.e., public health surveillance, which is distinct from individual prediction; it involves identifying patterns of potential elevated risk in communities and guiding public health action. With the proper methods, routine data can reveal relationships invisible in isolation, illuminating how early signals cluster, how interventions change trajectories, and how prevention can be timed. Early detection turns existing information into foresight, enabling health systems to act before greater harm occurs.

Rio de Janeiro, Brazil: Protecting communities by transforming siloed and fragmented data into proactive public health intelligence

In one of Latin America's largest and most complex cities, multi-sector data consisting of millions of records held by national and municipal systems were not digitally connected, making it hard to detect outbreaks, track risks, protect citizens or plan preventive measures. Supported in part by funding and technical assistance from the Data for Health Global Grants Program, the city's health secretariat established an Epidemiological Intelligence Center (CIE) and created an integrated "data lake" that combines health-related and other sector datasets.[21] Automated pipelines in Python, SQL, and R now continuously extract, clean, harmonize and link records, creating a longitudinal digital cohort of more than 6.5 million residents in a single analytic environment.

That foundation has shifted how the city manages health threats. With integrated, near real-time data, CIE teams can monitor disease trends, model risk and detect anomalies with far greater precision. Predictive models have already been used to anticipate surges in respiratory infections in infants and to forecast increases in flu-like illness up to two weeks in advance. The same infrastructure allowed Rio to set up a complete mpox response dashboard within days of WHO's emergency declaration, and it is increasingly used as the default platform for new surveillance and analytics tools.

Climate-related health threats are now part of that portfolio. After the brutal November 2023 heat wave, estimated to have caused nearly 1,400 excess deaths, Rio developed an Extreme Heat Response Protocol anchored in the CIE.[22] Meteorological data and heat indices from city sensors are combined with data on emergency visits, hospital admissions and mortality trends to model risk several days ahead. When thresholds are reached, the system triggers graded alert levels linked to specific actions: targeted WhatsApp and SMS messages, opening of cooling and hydration centers, stocking of primary-care clinics, and outreach in favelas such as Rocinha to check on older adults, children, and bedridden patients during dangerous heat.[23] Tested during the 2025 pre-Carnival period, this approach allowed Rio to keep its signature celebrations while reducing avoidable health risks.

Recife, Brazil: Preventing harm through early risk identification for gender-based violence and suicide

Early signs of risk often go unnoticed within routine care delivery. This gap appears across many public health issues, including suicide and gender-based violence (GBV). Suicide claims more than 727,000 lives every year, with nearly three-quarters of these deaths occurring in low- and middle-income countries. GBV affects one in three women worldwide, yet only a small fraction of cases are reported.[24] Tragically, signals of risk are typically missed, and cases become known when women and adolescents appear in emergency rooms, are hospitalized, or die.[25]

Recife's innovation began with the recognition that risk information already exists in routine primary care, community health and other public health and non-health sector datasets. Vital Strategies, FrameNet Brasil and the municipal health department used a data-matching method to link four existing systems: violence notifications (SINAN), mortality data (SIM), hospital records (SIH/SUS), and primary-care electronic records (e-SUS) to track encounters over time. Through data integration and linkage, and incorporation of information from unstructured clinical text, retrospective analysis powered by AI revealed previously invisible risk patterns. The analysis identified 2,174 additional cases of self-harm and 1,962 instances of suicidal ideation, representing a 44% increase in detected risk compared with conventional reporting. It is also estimated that 13% (around 80,000) of women who accessed primary care in 2022 were unidentified potential victims of violence.

Similarly, the team used AI-powered reading of open-text fields to examine routine primary-care records for linguistic and behavioral patterns indicating risk of suicidality. The model detected significantly more potential cases of harm than traditional surveillance and found a median 174-day gap between evidence of suicide ideation and self-harm attempts, and a 90-day window for gender-based violence. This same approach is now being tested for other issues, such as early detection of cancer.

Recife had years of routine consultations documented in continuous, digital primary-care records, including free-text clinical notes. Once the systems were connected, the patterns became discernible. This government-led, digitized, text-rich primary-care system, linked to surveillance, hospitalization and mortality data, is the foundational layer that enables more advanced AI analysis.

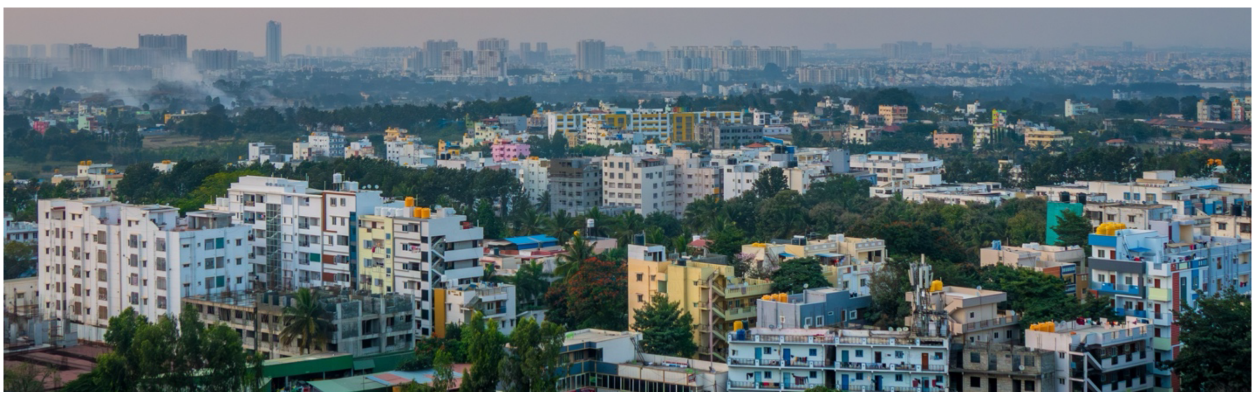
Rwanda: Promoting health objectives and national priorities through foundational digital and data systems investments

Rwanda is developing a health intelligence system on top of a deliberate digital build-out: a $200 million national digital acceleration program to expand broadband, upgrade digital ID and civil registration, and digitize public services at scale.[26,27,28] In this landscape, "foundational data systems" are treated as public goods: government-owned, government-led platforms that are digitalized, operate at a national scale, and can safely anchor AI. A core component is the National Centralized and Integrated Civil Registration and Vital Statistics (NCI-CRVS) system, built and governed by the National Identification Agency.[29] Rwanda's CRVS reform, which Vital Strategies has supported since 2016, is one of the most ambitious on the continent: The country is digitizing every birth, death and ID document, including historical records dating back to the 1950s, and linking them to a unified population register and a national digital ID.[30] The NCI-CRVS is now operational across health facilities, local cells, and embassies abroad, producing continuous data flows.[31] Events are coded to common standards and stored in formats that permit disaggregation by age, sex, geography, and other equity-relevant variables, making it a genuinely population-based and equity-ready system. When a birth is registered, it can automatically trigger enrollment in downstream systems such as electronic immunization registries; when a death is registered, linked IDs can be deactivated and mortality statistics updated in near real time. What emerges is a scalable, sustainable data backbone for targeting services, cleaning program rolls and conducting distributional analyses.

The Health Intelligence Center, established in April 2025, is designed to sit directly on this data backbone and turn it into usable intelligence. The Center consolidates real-time data from DHIS2, electronic medical records, logistics and supply-chain tools, emergency services and community reporting systems, using a six-layer architecture. It starts at the **source layer**, where systems like DHIS2, electronic medical records (eBuzima, cEMR), CRVS, eLMIS, WelTel, Emergency Medical Services, HWMS, and major surveys generate data. These feeds enter the **ingestion and transformation layer**, which standardizes and cleans them so they can be reliably combined.

Cleaned streams pass into a **landing zone**, a replication layer that temporarily stores raw input and preserves originals while they are processed.

From there, they flow into the **data lake**, where records from different systems are validated, linked and aggregated into integrated datasets, including those anchored in births and deaths from CRVS. These curated datasets are stored in a secure, scalable data storage layer that serves as the platform's operational memory. Finally, the **presentation layer** turns this into usable intelligence: dashboards, reports and analytic views for internal teams, plus Application Programming Interfaces (APIs)[32] that allow approved external users and tools, including AI models, to draw on a single, coherent picture of the health system. CRVS provides the core population frame in this structure: births, deaths and causes of death serve as denominators, and a continuously updated map shows who is at risk, where, and from what. This allows AI models for surveillance, forecasting and resource allocation to run on inclusive, continuous, government-led, population-level data rather than fragmented project databases.



India: Foundational digital public infrastructure

India's health system has embarked on a deliberate transformation from fragmented, facility-based data silos to a **coherent, federated digital ecosystem capable of powering public health intelligence at scale**. This transition is rooted in the Ayushman Bharat Digital Mission (ABDM)**,** a government-led initiative designed to create the digital backbone necessary for integrated service delivery, real-time visibility and data reuse across the health system. ABDM is positioned as a core component of India's **Digital Public Infrastructure (DPI)**, aligning health records, registries and consent-based data exchange with broader national identity and services infrastructure such as Aadhaar and UPI.[33] [34] ABDM's architecture is explicitly **citizen-centric**: individuals are treated as the **owners of their health data**, enabled through unique **Ayushman Bharat Health Accounts (ABHA)** and **Personal Health Records (PHRs)** that can be securely linked, accessed and shared across settings only when the individual authorizes it.[35] Emerging uses of AI in India's health ecosystem—including advanced, data-driven screening and early detection approaches—show potential to support earlier identification and personalized management of noncommunicable diseases such as diabetes, while interoperable, longitudinal digital health records enabled by the Ayushman Bharat Digital Mission provide the structured individual data that make scalable, preventive AI-enabled interventions possible.[36]

AI-Enabled Frontline Support & Service Delivery: eSanjeevani

The national telemedicine platform **eSanjeevani** illustrates how digital foundations can power **AI for Frontline Worker Support and Service Delivery (Decision Support Systems)** at scale. Designed as a government-owned platform under ABDM, eSanjeevani connects village-level access points with clinicians in secondary and tertiary facilities, embedding standardized electronic medical records into routine consultations. As of Nov. 23, 2025, the platform had facilitated more than 43 crore (430 million) teleconsultations across all 28 states and eight Union Territories.[37] Data captured during these interactions is interoperable through the ABDM API framework and tied to ABHA-linked records, creating **structured, consented data flows** across the continuum of care. Within this environment, **AI-enabled decision support tools** are integrated into clinical workflows, assisting frontline providers with triage, referral decisions and management of chronic conditions. These tools help standardize quality across settings, reduce unwarranted variation in care, and enhance clinical decision-making where skilled human resources are unevenly distributed.[38] Since the integration of the Clinical Decision Support System (CDSS) in April 2023, till November 2025, the eSanjeevani system has supported more than 282 million consultations. This shift moves data from an administrative by-product to a **continuous, longitudinal asset** that informs policy, planning and resource allocation across levels of government.[39]

CoWIN as System Intelligence & Administrative Digitalization

Another powerful example of foundational infrastructure enabling system insight is CoWIN, India's national vaccination platform. Built on open standards and interoperable modules, CoWIN captures registration, appointment scheduling, dose administration, certification and adverse event reporting in a unified digital environment. Its APIs integrate with other digital assets, including Aadhaar identity verification and digital credential services, ensuring that vaccination data is trusted and reusable.[40] In the context of the pandemic, CoWIN exemplified AI for System Intelligence, Policy and Planning (Decision Support + Reinforcement Learning) by providing real-time visibility into vaccine supply, uptake, coverage and demographic patterns across regions.[41] This data, presented as a national **"single source of truth,"** allowed policymakers and health managers to monitor performance in real time and adapt strategies accordingly.[42] Concurrently, the platform's digitization of operational workflows, such as automated scheduling, certification and adverse event reporting, illustrates Administrative Intelligence and Digitalization, in which structured, consistent data flows replace manual processes and create the digital fabric necessary for downstream analytics and learning. Because CoWIN was integrated into the ABDM ecosystem rather than operating independently, its core architecture was repurposed for routine immunization programs, demonstrating how crisis-driven digital systems can become permanent infrastructure for continuous service delivery and intelligence generation.[43] CoWIN's success is reflected in its scale: 950 million citizens are registered, and more than 1.6 billion vaccine doses have been administered and recorded. Of approximately 47,000 vaccination sessions, 73% were held in rural areas. Through assisted registration, coverage in hard-to-reach tribal communities surpassed the national average, demonstrating the platform's contribution to health equity.[44]

Taken together, these developments demonstrate that **foundational digital public infrastructure is the prerequisite for scalable AI and intelligence use cases** in public health. Where the Indian health system traditionally relied on fragmented paper records or disconnected digital silos, it is now building an **integrated, consent-driven data ecosystem** that can support insight generation from primary care to national program performance without creating new silos or bypassing individual rights. Programs like Ayushman Bharat have made health care more accessible to economically vulnerable populations by enabling individuals to access medical services without depleting personal savings, thereby contributing significantly to the overall decline in out-of-pocket expenditures.

Foundational Readiness Scan: Sub-Saharan Africa Cross-Country Snapshot

To understand how prepared different countries are to optimize the use of AI in public health, we compiled an **AI Foundational Readiness Scan** for a total of 63 countries—**all African countries and a small set of non-African countries in the Global South (South America, Asia and the Middle East), including Brazil, Jordan, India, Cambodia, Sri Lanka, Bangladesh, Thailand, Indonesia and Paraguay.** The scan is **directional, not diagnostic**. It is based entirely on a desk review of public sources, including national AI policy trackers. Scores from these sources may lag recent reforms, miss subnational variation, or differ from how governments describe their own systems. The scan includes five groups of indicators that together shape foundational AI readiness:

- **AI Policy:** Whether a country has a national AI policy or strategy, whether health is explicitly included, what type of document it is (strategy, framework, national policy), and its status (adopted, draft or started). These columns indicate whether AI is formally on the agenda and how visible health is, without judging policy quality or implementation.
- **Connectivity:** IDI connectivity score 2025 was used as a proxy for digital infrastructure and access. It assesses internet penetration, mobile coverage, and basic ICT capacity, which determine whether AI tools that rely on connectivity can function in practice.[45]
- **Interoperability (Digital Health):** An interoperability score drawn from the Global Digital Health Monitor (GDHM) tracks how far countries have progressed in integrating digital health systems and enabling routine data exchange across platforms.
- **Data:** Recognizing that it does not capture every dimension of data quality, the indicator "% *availability of recent data to monitor health-related SDGs*" from the WHO SCORE framework provides a simple gauge of how complete and up-to-date core health statistics (mortality, service coverage, risk factors) are.
- **Workforce (Health and Digital Health):** World Bank health care workforce density serves as a proxy for the strength of the clinical workforce.[46] A digital health workforce maturity score uses the GDHM Workforce domain, which averages four indicators: digital health integration into pre-service training; digital health integration into in-service training; formal training programs that produce a dedicated digital health workforce; and the maturity of public-sector digital health career paths.

Across the 63 countries, the scan shows a consistent pattern: **Policy intent is emerging faster than systems**. Roughly one-third of countries have adopted an AI policy, but **digital connectivity remains uneven**, **interoperability is partial in many settings**, **core health data are incomplete** in a significant subset of countries, and **both clinical and digital health workforce capacity remain thin**. The scan provides a high-level map of foundational strengths and gaps to guide where AI ambition is realistic today and where investments in data, systems and skills must come first.

Detailed country scores and sources are presented in **Appendix 2, "Foundational AI Readiness by Country."**

Use-Case Prerequisites Matrix

As part of the consultation process for this report, a use-case prerequisites matrix was developed to examine the system conditions under which artificial intelligence could generate durable public health value. The matrix was informed by a structured synthesis of inputs from a facilitated convening at the Global Digital Health Forum, complemented by targeted expert consultations and desk-based review. Rather than cataloging individual AI tools, the exercise focused on how different categories of AI use operate in practice and on the underlying digital, institutional, and governance conditions required for them to function safely, effectively, and at scale. Participants engaged across multiple public health domains with a shared emphasis on embedding AI into routine public health intelligence and service delivery functions, rather than deploying it as a standalone or experimental innovation.

Building on this process, the matrix organizes recurring prerequisites across AI use cases and distinguishes between the minimum conditions needed to **enable** a use case, those that **drive/accelerate** performance and adoption, and those required for **sustained, system-wide** scale. The key insights derived from this analysis are summarized below.

The matrix reflects how AI use cases mature over time. Minimum conditions enable basic operation; accelerators improve accuracy, adoption and efficiency through integration and workforce use; and scale-critical foundations determine whether AI can be embedded in routine public health systems.

- **Digitalization:** Across use cases, the matrix underscores that AI delivers public health value only when it is layered onto sufficiently digitized systems. Routine digital data generation through surveillance, clinical workflows, registries, administrative processes and communication platforms is a prerequisite for AI to function reliably.
- **Shared system dependencies:** Despite functional differences, most use cases depend on the same system-level enablers built on **digitized foundations**, including **interoperable data flows, standardized records, governance for data access and use, and sustained financing for digital operations**.
- **Decision linkage:** AI outputs such as alerts, predictions or classifications only produce value when connected to defined decisions, escalation pathways or service responses. Without this linkage, AI generates information without operational impact.
- **Institutionalization:** As AI use expands, durability depends on government ownership of digital architecture, integration into existing public health systems, regulatory oversight, and institutional capacity to manage, maintain, and adapt digitized systems over time.

The full Tiered Prerequisites Matrix for AI Use Cases in Public Health is presented in Appendix 4.

Discussion & Call to Action: A Framework for AI-Ready Public Health Data Systems

These findings and insights highlight a critical principle that is not always emphasized in the norm-setting, decision-making and resourcing discussions that are shaping the future of AI in public health: **High-quality, trustworthy, publicly governed, and country-owned data must be a central tenet of foundational public health data systems if we are to capture the promise of artificial intelligence for public health**. Before algorithms, models, or interactive dashboards, there must be a core of reliable data systems that accurately capture how populations experience health and disease over time.[47]

Across regions, participants described readiness not as a single benchmark but as a set of **preconditions** that determine whether AI will become a practical public health tool or an expensive experiment. The interviews underscore the fact that countries want AI to serve national priorities, reinforce—not fragment—core public health functions, and operate within trusted, accountable systems. This requires re-centering the discussion away from tools and toward the long-term data and institutional investments that make public health intelligence possible.

Drawing on this evidence, three principles provide a clear path forward for governments, funders and partners seeking to accelerate responsible AI adoption in public health:

Public health data strategies must be sustainable Ensure financing and workforce capacity, not just for initial investments but also for continued maintenance.	**Public health data structures must be government-owned** Institutionalize governance and oversight that protects sovereignty and builds public trust.	**Public health data systems must be comprehensive, inclusive, and contextualized** Treat data and digital systems as national infrastructure, not stand-alone, temporary projects.

1. Public Health Data Strategies Must Be Sustainable

Sustainability emerged as one of the most consistent themes across conversations. Governments stressed that AI readiness cannot depend on short-term pilots, isolated platforms, or donor-funded tools that collapse once projects end. As several respondents put it, *"The technology is the easy part; sustaining it is the real challenge."* Sustainability requires:

- **Long-term domestic financing** that funds hosting, maintenance, updates, connectivity and workforce, not just the initial build.
- **Integrated national budgets and cost plans** that prevent pilots from becoming stranded.
- **Investments in infrastructure** such as reliable power, local data centers, cloud hosting rules and country-owned computing resources.

- **Technical capacity within ministries** to evaluate, implement, monitor and iterate systems over time.

Without these elements, AI tools remain fragile, dependent on external actors, or functional only in demonstration settings. Sustained investment is what transforms prototypes into public value.

2. Public Health Data Structures Must Be Government-Owned and Publicly Governed

Interviewees were unequivocal: Countries cannot govern what they do not control. Sovereignty, trust and long-term value depend on governments owning the architecture identifiers, platforms, rules, standards, hosting decisions and procurement terms that underpin digital and AI systems. Government ownership assures that:

- AI aligns with national priorities rather than vendor or donor interests.
- Data access, consent and secondary use are subject to public oversight.
- Countries avoid vendor lock-in and retain control over model evolution.
- Systems can be pressure-tested and adapted to domestic realities.
- Accountability mechanisms and ethical guardrails reflect local values.

Respondents also emphasized that public governance is crucial for legitimacy, particularly when AI relies on sensitive or population-wide data. Public health intelligence must remain a public good that is planned, steered and safeguarded by the state.

As countries expand digitized health records, **distinctions between electronic health records (EHRs), managed by providers to support system functions, and personal health records (PHRs),** which center on individual access and control over data sharing, become increasingly important. AI-enabled systems must clearly define authority, consent and data portability. Without this clarity, digitization risks concentrating control without sufficient safeguards. Public governance, therefore, requires more than state ownership. Transparent consent frameworks, independent oversight, and participatory mechanisms are essential for creating checks and balances around the public's data. As AI increasingly relies on population-level information, these safeguards help ensure that digital and AI infrastructures function as public goods rather than opaque systems beyond democratic scrutiny.

3. Public Health Data Systems Must Be Comprehensive, Inclusive and Contextualized

For AI to strengthen, not stratify, public health outcomes, countries need data systems that reflect **everyone**, not just the digitally connected. Rural communities, informal settlements, lower-income households, people with disabilities, adolescents, linguistic minorities and displaced populations are at the most significant risk of being excluded from the datasets that feed AI models. Participants emphasized that **equitable AI requires equitable data infrastructure**. This means:

- National systems capable of covering the entire population, regardless of geography or service contact.
- Continuous, routine data flows that allow for early warning, forecasting and timely policy response.
- Harmonized standards to support disaggregation by age, sex, geography and other equity-relevant dimensions.
- Inclusion of local languages, cultural norms, digital behaviors and contextual knowledge in data capture and analytic design.
- Infrastructure investments, especially connectivity, so that marginalized communities are visible in national intelligence systems.

When foundational data systems are inclusive and contextualized, they become the backbone for more equitable models and more precise, targeted policy responses. AI applications built on these systems help governments identify who is at risk, why, and what interventions can close the gap.

Conclusion

Artificial intelligence will not fix fragile public health systems. But it can make systems brighter, faster and fairer when the right foundations are in place. The future of AI in public health should not be judged by how many pilots are launched, but by whether countries have built the data infrastructure, governance capacity and sustained institutional muscle needed for AI to deliver public value at scale.

When foundational data systems are treated as national public goods, and are digitalized, government-owned, inclusive and sustainably financed, they do more than support today's programs: **They determine who will be visible to tomorrow's models, whose experience will shape predictions, and who will benefit from the decisions that follow**. The use cases emerging today are early signals of what intelligent public health systems can achieve when built on strong foundations. Whether they remain isolated experiments or mature into a new normal depends on the decisions that countries, partners and funders make now.

Getting the foundations right will determine whether AI deepens fragmentation and inequities or helps build public health intelligence that makes it easier for everyone, everywhere, to live their healthiest lives.

Appendices

Appendix 1. Foundations & Futures: Thematic Interview Analysis

Findings in Tables 1a-1c draw on a rapid, cross-case qualitative synthesis of key informant interviews and stakeholder consultations. It also includes a country-specific analysis for India.

Summary of interview respondents*

Respondent category	Examples of affiliations	Regions represented	Roles/titles	Number of respondents
Government	**Ministries of Health**	Nigeria, Kenya, Cameroon, Paraguay, Jordan, India	Technical Advisors; Director of Strategic Information; Director of Policy and Research; Health Commissioner	7
Intergovernmental organizations	**World Health Organization and World Bank**	Global, Latin America, Sub-Saharan Africa	Executive Director, Health Emergencies Program; Director, Digital Health and Innovation; Senior Health Specialist;	3
Thought leaders	**Global, regional, and national NGOs, academic institutions, innovation centers, and think tanks**	Global, USA, Nigeria, South Africa, Sub-Saharan Africa, UK, Rwanda, Brazil, India	Chief Executive Officers; Chief Health Officer; Co-Founder; Vice President, Strategy and Partnerships; Public Health Physician and Urban Epidemiologist; President and CEO; Fellow, Global Development; Director	11

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We coded excerpts into a structured matrix and then applied inductive thematic analysis to identify recurring patterns in opportunities, gaps, risks and enablers for AI in public health across contexts. Codes were iteratively clustered into higher-order themes (e.g., foundational data systems, governance, human capacity, use cases) and subthemes, with constant comparison across regions and actor groups to test whether patterns were shared, divergent or outlier-specific.

The **"Cross-Conversations Rapid Synthesis"** column reflects only themes observed across multiple countries and stakeholder types and is validated through internal reviewer discussions rather than single-source anecdotes.

Table 1a: Current State Findings

Theme	Subtheme	Cross-Conversations Rapid Synthesis
Critical Building Blocks	**Foundational Data Systems & Interoperability**	Shared across ministries, practitioners and global experts: Data systems are fragmented, incomplete and not interoperable. DHIS2 coexists with donor-specific systems, creating duplicated and siloed data. Rural and vulnerable populations have the least visibility into their data. Many facilities still erase data due to limited storage. Countries lack national interoperability frameworks, shared identifiers and strong vital statistics. All groups link AI readiness directly to the maturity and connectedness of these foundational systems.
	Governance, Legal & Policy Frameworks	Respondents across Africa, WHO, and digital health implementers repeatedly noted that digital strategies exist but rarely include AI. AI governance structures are either early-stage or absent, and data protection enforcement is inconsistent. Countries rely heavily on WHO/UNESCO ethical guidance. There is broad agreement that stronger national laws, harmonized policies, and clear rules for data access, consent, and secondary use are essential preconditions for AI.
	Institutional Ownership & Coordination	Multiple respondents described weak coordination and fragmented ownership within ministries. Governments want to lead but lack clear mandates, financing, or dedicated AI units. Pilot fragmentation ("pilotitis") and partner-driven implementation still dominate. Kenya's digital health structures demonstrate stronger readiness; most countries lack similar institutional setups. Shared pattern: Without central leadership and alignment, AI remains piecemeal.
	Human Capacity, Digital Literacy & Inclusion	A widely shared barrier: limited AI/ML expertise and low digital literacy among health workers and ministry staff. Many still prefer paper-based routines. Talent programs exist in some countries, but are still in their early stages. End-user inclusion also shapes readiness; respondents stressed differences in youth digital behavior, rural access, language, disability needs and device ownership. AI solutions often fail when they assume levels of digital readiness that populations lack.
	Context-First, Problem-Driven Design	Ministries, WHO, and implementers agreed that AI adoption must begin with national public health priorities. Several respondents said some problems "are not digital" or "not AI problems." Countries with intermediate readiness often lack clarity on where to start, reinforcing that defining the problem is essential before choosing AI tools.
	Digital Public Infrastructure	Multiple respondents, including WHO and technical experts, framed foundational registries (ID, CRVS, facility lists, workforce registries) and national standards as long-term infrastructure required for AI to work. Countries with these systems in place absorbed digital tools more effectively during COVID. Shared pattern: AI cannot scale without these long-horizon foundations.
Promising Use Cases	**Predictive Analytics & Early Warning Systems**	Countries and experts consistently see predictive analytics as the strongest and most immediate AI opportunity. Predictive tools are already used to forecast missed antenatal care and HIV visits, detect outbreaks and issue early warnings for health crises. Outlier examples fit naturally here, including detecting early GBV risk in patient narratives, mapping underserved zones with low vaccine coverage, and combining biometric trends (BMI, age, temperature) to anticipate outbreaks. Cross-sector signals, such as linking school performance with clinical visit patterns, reinforce the potential for early detection of social harm. This theme captures all opportunities for "anticipatory intelligence" that were raised.
	Diagnostic Imaging Support (TB, Cancer, COVID, CT/X-ray)	Across regions, AI's promise in radiology is a repeated, high-impact opportunity. Countries lack radiologists, and AI can automate first-pass triage for TB, cancer, CT scans, and chest X-rays. AI helps eliminate obvious negatives, prioritize likely positives, and reduce the burden on overstretched specialists. This remains a clean, distinct theme; outliers did not extend it beyond imaging.

Theme	Subtheme	Cross-Conversations Rapid Synthesis
	Data Quality Automation & Population-Level Analytics	Respondents emphasized that AI's value is magnified when it helps structure and clean large, messy datasets. AI can automate mortality coding (IRIS/PAHO), classify administrative documents, deduplicate records, correct diagnostic codes, and transform analog archives into structured, analyzable data. This category also absorbs outliers related to automated death classification, public servant document processing, and the production of population-level insights that improve planning and surveillance.
	Workflow Optimization & Administrative Efficiency	A central cross-cutting theme: AI reduces administrative overload, freeing up human time. Ministries and implementers highlighted AI for insurance fraud detection, coding error flagging, automated helpdesk triage (e.g., WhatsApp scaling), clinical documentation support, and community health worker workload reduction. These outlier examples fit seamlessly: productivity tools for public servants and systems that automatically route administrative tasks. Together they form a coherent theme around operational efficiency.
	Hybrid Human–AI Support for Frontline Workers & Clinicians	Multiple respondents stressed that AI's most significant value is in *augmenting*, not replacing, human expertise. This includes CHW support tools in Tanzania and Ethiopia, LLM-based assistants for health workers, triage tools that route complex cases to human responders, and GBV risk indicators that trigger human follow-up. Social-service navigation tools (e.g., SNAP assistance) also belong here: AI organizes information, humans provide final judgment. Outliers strengthen rather than shift the theme.
	Behavior Change, Personalization & User-Facing Chatbots	Youth-facing platforms, African innovators and global digital implementers all identified chatbots as a powerful opportunity—especially when tuned to local languages, accents, spelling patterns and cultural nuances. Expanded examples include distress detection among youth, voice interfaces for low-literacy populations and WhatsApp-scale personalization for millions. AI enables deeper tailoring of communication, extending well beyond deterministic messaging and making behavior change interventions more effective.
	Cross-Sector Intelligence for Public Planning & Social Protection	Several respondents highlighted the power of linking health, education, social protection, and demographic data. This theme now cleanly incorporates outliers such as GBV prediction using school performance plus clinical data, mapping underserved territories, identifying populations at risk of falling through the cracks, and enabling AI-powered navigation of social benefits (e.g., SNAP). The theme captures how multisectoral data fusion can drive more targeted, equitable planning across government.

Table 1b: Insights & Recommendations

Theme	Subtheme	Cross-Conversations Rapid Synthesis
Gaps & Needs	**Interoperability & Integrated Data Systems**	A universally reported gap: fragmented systems, the absence of unique IDs, weak registries, and the lack of national interoperability frameworks. Ministries and implementers emphasized that data sits in parallel donor databases, limiting analytics and making cross-disease or cross-facility insights impossible. Poor rural connectivity and paper-based workflows further constrain system integration.
	High-Quality, Structured & Representative Data	Repeated across WHO, Data.org, ministries of health and implementers: Data quality is the foundational barrier. Unstructured datasets, inconsistent tagging, incomplete records, and low visibility of vulnerable populations undermine model performance. Power outages, storage constraints and data deletion practices worsen the challenge. AI cannot function reliably without substantial investment in data completeness and quality.
	Workforce Capacity, Digital Literacy & Skills Gaps	Shared widely: Health workers, policymakers and technical teams lack AI/ML literacy. Ministries noted limited internal engineering expertise; implementers highlighted that frontline workers still rely heavily on paper. Policymakers often cannot evaluate AI proposals or ask the right questions. Continuous, tiered training—not one-off workshops—is needed for sustained readiness.
	Governance Operationalization, Oversight & Enforcement	Multiple respondents stressed that policies exist “on paper” but lack enforcement. AI ethics, data protection rules and digital health review processes are not operationalized. There are gaps in ongoing model monitoring, inconsistent compliance and no precise mechanisms for auditing AI tools. Governments remain reactive rather than proactive.
	Sustainable Financing, Integration into Budgets & Long-Term Ownership	Cross-cutting: Pilots collapse when donor funding ends because scale, maintenance, and integration are not funded. Governments lack domestic budget lines for AI and digital infrastructure. Implementers emphasized that funding typically covers “the tech,” not implementation, integration, or demand generation—the very elements required for scale.
	Equity, Inclusion & the Digital Determinants of Readiness	Repeated across youth platforms, by gender/SRH implementers and among data experts: Women, girls, residents of rural communities, older people, and persons with disabilities are at risk of exclusion. Language, device access, trust and safety concerns create uneven readiness. Lack of inclusive datasets further deepens inequity. AI must intentionally address digital divides rather than reinforce them.
Concerns & Risks	**Data Privacy, Security & Sovereignty Risks**	Repeated concerns across ministries of health, WHO, Data.org, Brazil, Nigeria: data leaks, commercial misuse, nonconsensual LLM training, weak privacy enforcement, sensitive data exposure (HIV, SRH, identity). Countries fear losing control of data to external vendors. Data hosting abroad, data repatriation disputes, and unclear ownership after partnerships end appear across multiple contexts.
	Fragmentation, Weak Data Quality & Model Misalignment	Shared pattern across all regions: Fragmented systems and low-quality or incomplete data create unreliable AI outputs. Models trained on non-African or non-representative datasets consistently misfire—from skin-tone misdiagnoses to predictive models that fail to capture local patterns. AI tools built externally rarely calibrate to local context or population needs.
	Sustainability, Cost & “Pilotitis” Risks	Multiple respondents flagged the same issue: Pilots don’t scale, vendors remove technology after projects end, and governments can’t afford computing systems or maintenance. Donor-driven AI creates dependency without long-term planning. Even strong tools break once funding ends. High computing costs make a national scale unfeasible.
	Bias, Inequity & Exclusion Risks	Experts working with vulnerable groups, noncommunicable disease leads, WHO, and data scientists all flagged bias as a significant risk. Underserved populations have the poorest data, which worsens inequities. AI risks amplifying discrimination—from dermatology misclassification to SRH exposure risks. The fear that AI widens the gap rather than closing it is widespread.

Theme	Subtheme	Cross-Conversations Rapid Synthesis
	Workforce Mistrust, Job Loss Anxiety & Low Digital Familiarity	Health workers, ministry staff and local experts repeatedly raised fears that AI will replace them. This is coupled with low digital literacy and poor understanding of AI systems. Resistance mirrors earlier computerization phases. Concerns about accountability when AI contradicts human judgment show up across countries.
	Lack of Regulation, Oversight & Evaluation Capacity	A shared pattern: AI models operate in "black boxes," and most countries lack the regulatory systems to evaluate or audit them. Governments worry about unpredictable behavior (especially from generative AI), unclear liability for harmful outcomes, and NGOs deploying unmonitored tools. WHO emphasized that regulatory systems are not built for the speed of AI.
	Ethical Risks for Vulnerable Populations	Youth platforms, SRH implementers, and Brazil's rights experts consistently raised concerns: AI can expose girls, refugees and marginalized groups to harm if wrong actors access data; some questions/topics are unsafe; anonymization is not foolproof. Fear of surveillance, extortion or stigma (e.g., HIV data leaks) appears across contexts.
	Vendor Lock-In, Power Asymmetry & Loss of Agency	WHO, ministries of health and African digital experts all highlighted the risk of relying on proprietary systems that governments cannot modify or interrogate. Countries fear being trapped in expensive one-off solutions that cannot be scaled or changed. Partnerships without clear ownership or IP agreements weaken the national agency.
Enablers & Drivers	**Foundational Digital & Computing Infrastructure (DPI)**	Experts and ministries stressed that durable AI capacity depends on shared infrastructure: robust data centers, reliable power, broadband connectivity and, in some cases, national or regional supercomputers. Local clouds and integrated data pipelines were described as "foundational investments" that serve many sectors, not just health. Countries that direct vertical (e.g., HIV) funds into integrated platforms rather than siloed systems are seen as moving in the right direction.
	Laws, Policies & National Strategies for AI	Across Paraguay, Kenya and the African region, a recurring enabler is explicit policy scaffolding: national AI or digital strategies, AI-relevant laws, and sector-specific guidance. Countries want frameworks that are broad enough to be flexible yet anchored in ethics and technical understanding. Global norms (WHO, UNESCO, Africa CDC strategies) provide a reference point, but respondents emphasized the need for domestically owned rules and review processes.
	Integration into National Systems & Budgets	Ministries consistently highlighted that AI must sit inside national health information systems (SNIS, NHIS, community health platforms) rather than as one-off pilots. Direct budget allocations, tax-funded models and long-term bilateral support are seen as key to sustainability. Implementers stressed that funding must cover integration, demand generation and maintenance, not just the initial build.
	Regional & South-South Collaboration and Shared Standards	Respondents pointed to regional hubs, cross-country collaborations (e.g., Paraguay-Colombia on mortality classification), and work with Africa CDC, WHO and other regional bodies as primary enablers. No single country will have all the data or expertise; peer learning, shared taxonomies, and regional standards help countries move faster and with more bargaining power.
	Embedded Talent, Co-Design & Human-in-the-Loop Models	A recurring enabler is putting skilled people *inside* government and frontline teams: AI fellows embedded in ministries; councils that include local women, health workers, technologists and policymakers; and co-design processes where clinicians and implementers "break" and refine tools. Human-in-the-loop models are seen as both a safety mechanism and a way to build ownership and practical capacity.
	Trust, Culture, Language & Youth-Centered Design	Trust emerges as a critical enabling condition: trusted brands with young people, clear consent flows, and products that speak local languages and dialects and align with digital habits. Teams invest in accents, spelling tolerance, and context-sensitive content so that users feel understood. This cultural and linguistic fit is repeatedly described as what turns technically sound tools into actually used and valued ones.

Theme	Subtheme	Cross-Conversations Rapid Synthesis
	Partnerships, Peer Networks & Communities of Practice	Ministries and implementers see value in partnerships that build local capacity rather than dropping in tools. Peer networks (such as Agency Fund-type communities) that share lessons, negotiate with vendors and co-solve common problems enable more innovative, cheaper and more scalable AI deployments. Mutually beneficial, reasonably priced arrangements are preferred over "golden handcuff" donations.
	Public Data Governance, Commons & Data Justice Approaches	Several respondents highlighted public data governance frameworks, data cooperatives, and "data justice" models as structural enablers. These approaches keep governments in the driver's seat on questions of who benefits from data, how value is shared, and how communities participate in decisions. When governance is built early around fairness and participation, it becomes easier to scale AI without losing legitimacy.

Table 1c: Governance & Legal Considerations

Theme	Subtheme	Cross-Conversations Rapid Synthesis
Governance & Legal	**Fragmented Governance & Lack of a Central Coordinating Authority**	Respondents across Paraguay, Kenya, Nigeria, and global actors consistently highlighted fragmented leadership. Ministries have digital initiatives dispersed across directorates, with no unified AI strategy or central entity to coordinate projects, standards, or partnerships. This leads to unaligned pilots, inconsistent decision-making, and limited national ownership over AI direction.
	Absence or Weakness of AI-Specific Legal & Regulatory Frameworks	Many countries lack AI laws altogether, and even where digital health laws exist (in Kenya and other parts of Africa), they do not cover AI model evaluation, bias assessment, or algorithmic risk management. Governments lack internal procedures for reviewing AI tools, vetting vendors, or setting conditions for model deployment. Policy frameworks tend to be reactive rather than anticipatory.
	Opaque Algorithms & Limited Model Transparency	Ministries and implementers repeatedly cited the inability to see inside models, understand how decisions are made, or verify outputs. Tools brought by partners often function as “black boxes”—with no visibility into their training data, calibration, or logic. This undermines trust, decision-making, and safety evaluations.
	Weak Enforcement of Existing Data Protection & Digital Policies	Even where laws or review processes exist, enforcement is inconsistent. Respondents emphasized gaps in monitoring compliance, in reviewing digital tools submitted to regulators, and in applying penalties for violations. Governments often lack the institutional power or capacity to ensure adherence by private actors or pilot implementers.
	Data Governance Gaps: Ownership, Hosting, Access & Exit Protocols	A cross-cutting concern: unclear rules on who owns data generated through AI projects, where it is stored, how long partners can access it, and what happens when pilots end. Several ministries have experienced data loss or a dependence on external hosting arrangements. This directly affects sovereignty, continuity, and national trust.
	Need for Ethical Oversight & Guardrails for AI Deployment	Respondents across WHO, ministries, and implementers stressed the absence of ethical review boards, model-specific approval processes, and guardrails against bias, safety risks, and context suitability. Countries lack mechanisms to monitor AI models after deployment continuously. Governance frameworks for adolescent-facing or sensitive data use are particularly underdeveloped.
	Public-Private Imbalance & Need for Stronger Contractual Protections	Governments rely heavily on private partners for AI development and deployment, but contracting often lacks clauses on data ownership, hosting, IP, transparency, and exit provisions. Respondents stressed the need for government-led negotiation power, stronger procurement criteria, and explicit data sovereignty protections.
	Need for Participatory, Transparent, Trust-Building Governance	A broad consensus: Legitimacy rests on the involvement of citizens, communities, and frontline workers. Respondents emphasized transparency, participatory data governance, and public input as essential for trust—especially when dealing with sensitive health data or youth-targeted AI.

Country Lens—India

As this analysis continues to evolve through additional convenings and consultations, early discussions with senior leaders in India's public health system provide an initial country-level lens on the themes presented in Tables 1a-1c. These discussions largely reinforced the relevance of the existing framework. Leaders consistently emphasized the centrality of foundational data systems, governance and stewardship, institutional ownership, workforce readiness, and human-AI interaction in shaping the feasibility and scalability of AI in public health. Fragmented data platforms, uneven digitization across states and facilities, and variable data quality were described as persistent constraints, with AI often making these gaps more visible rather than compensating for them. By making existing systemic gaps visible, AI is serving as a powerful diagnostic tool for the health system itself, guiding administrators and policymakers exactly where to focus their strengthening efforts. Across discussions, scale was framed less as a technical challenge and more as a function of alignment with national platforms, clarity of ownership across levels of government, and sustained institutional stewardship.

The conversations also reinforced the importance of problem-driven design and human-centered implementation. AI tools were viewed as credible when they were clearly tied to public health priorities, validated with system owners and domain experts, and integrated into existing workflows in ways that preserve professional judgment. Human-in-the-loop approaches were treated as necessary rather than optional, particularly given concerns around accountability, error handling, and model limitations. While these observations largely align with the cross-country synthesis, the discussions also surfaced a small number of operational and governance considerations that are not yet fully reflected in Tables 1a and 1c. Given the iterative nature of this document, these are treated as emerging signals rather than validated themes. They are presented separately below to preserve analytical rigor and to allow for future assessment as additional country lenses and convenings are incorporated.

Document Section	Subtheme	India-Specific Insight
1a: Current State Findings	Transparency	Digital and AI systems inherently create transparency. Dashboards and reports expose gaps and inefficiencies that manual systems previously hid, leading to transformative change in the health systems.
	Operational Data Readiness	Data readiness goes beyond completeness. Data needs to reflect real operating conditions, including different devices, operating systems, clinical and community settings, and how tools are used in practice.
1b: Insights & Recommendations	National Alignment for Scale	State pilots can work well locally, but if they are not aligned with national programs and platforms, they eventually face forced integration or discontinuation as national systems evolve.
	Prevention-Focused AI Gaps	There is limited investment in AI for prevention, behavior change, and mental health, even though these areas are where early intervention could reduce the long-term burden on the system. Solutions also need to work in local languages and privacy-sensitive formats.

1c: Governance & Legal Considerations	Bureaucratic Continuity	Continuity within the bureaucracy is a stronger predictor of scale than political support, which can change quickly. Long-term adoption depends on sustained administrative ownership.
	Policy Rigidity	Scaling AI is constrained less by technology or procurement and more by policy rigidity. Policies often need to change before standards and procurement mechanisms can function effectively.
	Anticipatory Governance	Key risks such as connectivity gaps, vendor dependency, and policy blockers need to be identified at the start and tracked continuously, rather than addressed only after projects run into problems.

Appendix 2: Foundational AI Readiness by Country

This table offers a **high-level, directional snapshot** of how African countries, along with selected comparator countries (India, Indonesia, Sri Lanka, Bangladesh, Thailand, Jordan, Brazil and Paraguay), are positioned to adopt AI in public health. It is built entirely from **internet searches and desk review of public sources**, not from country validation. As such, it should be read as **indicative, not definitive:** Values may lag behind recent reforms, miss subnational variation, or differ from how governments themselves describe their systems. Any country using this material should adapt or replace it with national data where possible.
The scan brings together five groups of indicators:

- **AI Policy:** The initial columns indicate whether a country has a national AI policy or strategy, if health is explicitly included, what type of document it is (e.g., strategy, framework, national policy), and its current status (adopted, draft, or not started). These entries primarily come from the ITU AI Policy Observatory, UNESCO's AI policy tracker, and official government websites, and are cross-verified, where possible, against the original policy PDFs. They are intended to show whether AI is part of the policy agenda and how prominently health is featured, not to assess policy quality or implementation.
- **Connectivity:** The **ICT Development Index (IDI) score** from the **International Telecommunication Union (ITU)** gives a broad measure of digital connectivity and infrastructure: internet access, mobile penetration, and basic ICT capacity. Higher scores suggest a more enabling digital environment for AI tools to function, particularly those that rely on online services or cloud connectivity. Where a 2025 value is not yet available, the most recent published score is used.
- The **Interoperability Score** is drawn from the **Global Digital Health Monitor (GDHM),** which is an interactive resource that supports countries in prioritizing and monitoring their digital health ecosystem. The score is a metric used to evaluate a country's digital health ecosystem.
- **Data:** The health-data column uses the "availability of latest data to monitor health-related SDGs" indicator from the **WHO SCORE Global Report** (2023). It provides a percentage estimate of how complete and up-to-date core health statistics are, including mortality, service coverage, and risk factors. Higher percentages indicate stronger foundational data for public health analytics and AI training, but they do not capture data quality across all program areas.
- **Workforce (Health and Digital Health):** Health Workforce uses **WHO Global Health Observatory/World Bank** data on the density of doctors, nurses, and midwives per 1,000 population, a proxy for the strength of the clinical workforce. The **Global Digital Health Monitor Workforce** domain assigns countries an average score of Phase 1-5 based on four indicators: digital health in preservice and in-service training, formal training programs that produce a digital health workforce, and the maturity of public-sector digital health careers.

Country	Policy			Connectivity	Interoperability	Health Data	Workforce	
	AI Policy (Yes/No)	Health Specified?	Policy Type	IDI Score 2025	Standards & Interoperability	WHO SCORE*	Health Workforce	Digital Health Workforce
Algeria	Yes Adopted	Indirect Mention	AI Strategy	86.1	-	56%	1	-
Angola	No	-	-	52.8	-	68%	0.2	-
Botswana	No-Draft	-	-	82.1	4	50%	0.4	2
Burkina Faso	No-Draft	-	-	-	2	62%	0.1	3
Benin	Yes Adopted	Yes	AI & Big Data Strategy	47.4	4	58%	0.2	2
Burundi	No	-	-	25.3	2	66%	0.1	3
Cabo Verde (Cape Verde)	No	-	-	80.6	2	73%	0.8	2
Cameroon	Yes Adopted	Yes	AI Strategy	46.3	2	70%	0.1	2
Central African Republic	No	-	-	-	2	28%	0	1
Chad	No-Draft	-	-	-	2	62%	0.1	2
Comoros	No	-	-	52.2	1	30%	0.4	1
DRC Congo	No-Draft	-	-	38	2	73%	0.2	2
Republic of the Congo	No	-	-	49.6	-	49%	0.2	-
Djibouti	No-Draft	-	-	64.4	-	37%	0.2	-
Egypt	Yes Adopted	Yes	AI Strategy	77.9	2	98%	0.7	3
Equatorial Guinea	No	-	-	45.5	-	23%	0.1	-
Eritrea	No	-	-	-	-	51%	0.1	-
Eswatini (Swaziland)	No	-	-	74.4	-	71%	1.6	-
Ethiopia	Yes Approved	Yes	AI Strategy	44	3	96%	0.1	5
Gabon	No-Draft	-	-	76.1	1	33%	0.5	1
Gambia	No	-	-	-	-	57%	0.1	-
Ghana	Yes-Adopted	Yes	AI Strategy	70.6	1	66%	0.1	3
Guinea	No	-	-	-	4	46%	0	4
Guinea-Bissau	No	-	-	39	1	53%	0.2	1
Ivory Coast	No-Draft	-	-	69.5	1	57%	0.2	2
Kenya	Yes-Adopted	Yes	AI Strategy	56	5	83%	0.1	2
Lesotho	Yes-Adopted	Yes	AI Policy	58.4	3	57%	0.2	2
Liberia	No-Draft	-	-	43.6	3	53%	0.2	3
Libya	Yes-Adopted	Yes	National AI Policy	87.8	-	69%	2.2	-
Madagascar	No	-	-	32.8	3	55%	0.2	2
Malawi	No	-	-	35.4	5	64%	0	4
Mali	No-Draft	-	-	42.9	2	57%	0.2	3
Mauritania	Yes-Adopted	Yes	AI Strategy	58	1	53%	0.2	1
Mauritius	Yes-Adopted	Yes	AI Strategy	86.3	-	72%	1.2	-

Country	Policy			Connectivity	Interoperability	Health Data	Workforce	
	AI Policy (Yes/No)	Health Specified?	Policy Type	IDI Score 2025	Standards & Interoperability	WHO SCORE*	Health Workforce	Digital Health Workforce
Morocco	No-Draft	-	-	88.2	1	96%	0.7	1
Mozambique	No	-	-	32.4	3	72%	0.1	2
Namibia	Yes-Adopted	Yes	AI Strategy	73.2	2	52%	0.5	2
Niger	No	-	-	-	3	60%	0	1
Nigeria	Yes Adopted	Yes	AI Strategy	52.9	3	51%	0.4	2
Rwanda	Yes Adopted	Yes	AI Policy	51.9	3	70%	0.1	3
São Tomé and Príncipe	No-Draft	-	-	57.1	2	66%	0.5	1
Senegal	Yes Adopted	Yes	AI Strategy	71.6	1	59%	0.1	2
Seychelles	No	-	-	82	-	76%	3.8	-
Sierra Leone	No	-	-	-	2	77%	0	2
Somalia	No	-	-	33.7	-	38%	0	-
South Africa	No-Draft	-	-	85	3	69%	0.8	2
South Sudan	No	-	-	-	-	34%	0	-
Sudan	No	-	-	-	-	89%	0.3	-
Tanzania	No-Draft	-	-	53.2	5	60%	0.1	2
Togo	No	-	-	47.2	1	54%	0.1	1
Tunisia	Yes Adopted	Yes	AI Strategy	79.6	-	78%	1.3	-
Uganda	No	-	-	42.4	3	88%	0.2	3
Zambia	Yes Adopted	Yes	AI Strategy	60.3	3	83%	0.3	2
Zimbabwe	Yes Adopted	Yes	AI Strategy	56.8	2	89%	0.2	3
Regional Comparators								
Brazil	Yes Adopted	Yes	AI Strategy	84.4	5	-	2.1	4
Paraguay	No	-	-	76.3	-	91%	3.9	-
Jordan	Yes Adopted	Yes	AI Strategy	84.7	2	81%	2.5	3
India	Yes-Adopted	Yes	AI Strategy	-	4	89%	0.7	-
Cambodia	No-Draft	-	-	77.4	2	87%	0.2	1
Indonesia	No-Draft	-	-	84.7	3	68%	0.7	3
Sri Lanka	No-Draft	-	-	71.4	3	94%	1.2	3
Bangladesh	No-Draft	-	-	64.9	2	91%	0.7	3
Thailand	Yes-Adopted	Yes	AI Strategy	91.9	3	83%	0.9	4

****Availability of the latest data to monitor health-related SDGs***

Appendix 3: Rapid Use-Case Landscape Scan (Africa+)

Methods: This landscape scan drew on **unsystematic exploratory searches** to surface how AI is being used in public health contexts across Africa. The aim was not completeness, but to capture the spread and character of activity already visible. The **GPT-5 Deep Research** feature served as the primary scanning tool, with iterative prompts used to identify emerging examples, early pilots, and national digital initiatives.

The process began with **independent scans of each African subregion**, Northern, Central, Eastern, Western and the Indian Ocean region, to build an initial view of patterns across contexts. This was followed by **country-by-country searches**, treating each country as its own case and identifying references to AI tools, digital health projects, pilots, or research efforts connected to public health. **A small set of non-African countries in the Global South (South America, Asia, and the Middle East), including Brazil, Jordan, India, Cambodia, Sri Lanka, Bangladesh, Thailand, Indonesia, and Paraguay, was also included.** These were incorporated because partnerships and active engagements provided direct access to examples. Their inclusion reflects **a purposeful selection based on relevance and availability, rather than a systematic regional search**. As relevant examples appeared, **follow-up scans** were run to clarify details, explore related work, and identify similar tools in neighboring settings. In some countries, follow-up depth increased due to existing engagement with governments or partners. In total, the search generated **277 entries**, which were reviewed and coded by AI technology type, public health relevance, use case focus, verification status, and activity status (active, pilot, or research phase). After excluding entries without a public-health function, **198 examples remained**. A **qualitative synthesis** of these examples highlighted recurring functional patterns. Clusters of similar activity began to appear across countries and regions. Patterns were examined in terms of what the tools were designed to do, the problems they targeted, and the types of data and workflows they relied on. Through this iterative comparison and regrouping, five broad functional themes consistently surfaced across the landscape. They formed the organizing structure for the subsequent use-case groupings below. In addition, we have added a similar landscape scan specific to India against the use-case groupings. It documents 37 active AI solutions currently being implemented across India, serving as a comprehensive baseline for our digital health road map.

Use Case Grouping	Description	Examples	India Specific Examples (OUTSIDE SEARCH)
AI-Enhanced Diagnostics & Screening at Scale	Using AI (mostly computer vision + some ML) to detect disease faster, more accurately, and in more places, especially where specialists are scarce. They include tools that analyze images, signals, or rapid tests to expand access to high-quality diagnostics, especially for **tuberculosis** (TB), malaria, cancer, and other priority conditions, often embedded in mobile or frontline services.	• **Infectious diseases:** CAD4TB, Qure.ai, national TB X-ray networks, mobile TB vans, digital X-rays with AI triage in rural clinics and prisons, TB in refugee and conflict settings. Triage huge volumes, catch cases radiologists miss, and reduce time from suspicion to treatment. Mobile malaria microscopy (smartphone + 3D-printed microscope), Noul digital malaria microscopes in Benin, Malariya Pi reading malaria RDTs. • **Oncology & other conditions:** Digital pathology (breast & cervical cancer labs), cancer screening in refugee camps. Snakebite identification app that uses image recognition to choose the correct antivenom. Radiology support for chest pathologies in conflict zones.	• **Infectious Disease:** qXR, Genki, digital X-rays with AI to triage and identify TB cases in rural settings. Screens huge volumes and gives result in less than a minute. Smartphone solutions like CATB, Swaasa analyzes cough sound to detect pulmonary TB. Shonit (SigTuple) is AI base application for automated blood smear analysis. It uses computer vision to detect malaria-infected red blood cells. Truenat enables evidence-based treatment decisions for TB, HIV, malaria, viral hepatitis, dengue, chikungunya, influenza, H1N1, HPV/cervical cancer, cholera, leprosy, etc. • **Oncology & other conditions:** Thermalytix uses thermal sensing for breast screening, deployed in community screening programs. cervAstra analyzes pap smear at point of care to detect cervical cancer. MadhuNetrAI

Use Case Grouping	Description	Examples	India Specific Examples (OUTSIDE SEARCH)
			enables nonspecialist health workers for AI-enabled diabetic retinopathy screening.
AI for Surveillance & Early Warning	Using AI (machine learning, predictive analytics, NLP, computer vision) to spot outbreaks early, forecast risks, and guide rapid public-health action. These systems analyze diverse data streams—health records, environmental signals, satellite imagery, wastewater, news reports—to detect unusual patterns before they escalate into full outbreaks. They typically scan open-source and health data to detect early signals, prioritize alerts, and support national epidemic preparedness.	• **Outbreak intelligence & Epidemic Early Warning:** EPIWATCH, EIOS + ML triage, National Health Intelligence Platforms/Centers, AI4PEP systems. • **Vector-borne & zoonotic disease forecasting** early warning for Rift Valley Fever; malaria forecasting models (e.g., XGBoost); dengue forecasting/nowcasting; schistosomiasis risk maps; zoonotic detection via DROMEDIC-AI. These tools help anticipate outbreaks weeks/months ahead using climate, mobility, livestock, and environmental data. • **Environmental & wastewater surveillance:** INTERACT waterborne pathogen dashboard, cholera outbreak prediction tools correlate wastewater signals with disease cases to map hotspots and trigger preventive action. • **Nutrition & health vulnerability forecasting models** predict acute malnutrition using health, satellite, and environmental data and support early, targeted interventions for at-risk populations.	• **Outbreak intelligence & Epidemic Early Warning:** Health Sentinel tool scans over 35,000 media sources and gives alerts to detect outbreaks early. IHIP government of India portal that provides real-time alerts to district surveillance officers. A mobile-based digital platform, Aarogya Setu, provided syndromic self-assessment data. EPIWATCH early warning system for epidemics, pandemics and other health events. • **Vector Borne & Zoonotic Disease Forecasting:** VECTRI malaria model uses daily temperatures, rainfall, soil moisture, population, etc. to forecast transmission. National Animal Disease Reporting System (NADRS) is digital animal disease reporting platform. • **Environmental & Wastewater Surveillance:** CPCB provides real-time monitoring and alerts for air pollution, IMD MausamGPT generative AI adviser that processes weather data to provide real-time disease risk alerts to state health departments.
AI for Public Communication & Behavior Change	Using generative AI and NLP chatbots to deliver personalized, culturally relevant health information at scale. These tools operate via WhatsApp/SMS, web platforms, and even radio, supporting behavior change and improving health literacy. Typically private, youth-friendly counseling on SRH and HIV prevention.	• **SRH & HIV communication:** Sophie Bot, Kiko, Weerwi, Self Cav HIV chatbot, SRH chatbot for adolescents with disabilities. • **Maternal health & parenting support:** Momconnect, Jacaranda PROMPTS AI-triage messages integrated into public facilities. Improves maternal and newborn outcomes through early triage and timely referrals. • **Health literacy & self-care:** Kem, ThutoHealth, DoxaCare, AwaDoc, Clafiya health info, DRRIYA assistant. 24/7 symptom guidance, immunization advice, and trusted health information. • **Mass communication with AI-tailoring:** Boresha Live AI malaria radio generates localized radio messaging, reaching millions with trusted malaria prevention advice.	• HIV and Sexual Health communication: Love matters India, "JUST ASK!"/ Khoolke Puchho, Yes4Me, SnehAI are chatbots targeting adolescents and young adults focusing on questions about sexual health. Yes4Me chatbot provides a risk assessment quiz and targets high-risk groups of MSM and transgender individuals. • **Maternal health and parenting support**: Kilkari 2.0 is mobile based Interactive Voice Response (IVR) and WhatsApp to deliver multimedia content and facilitate two-way communication. mMitra free mobile voice call service sending timed and targeted weekly/bi-weekly preventive care messages directly to the phones of enrolled women through pregnancy and infancy, in their chosen language and time slot. Khushi Baby (CHIP), An AI-integrated platform for ASHA workers that identifies high-risk maternal symptoms and automates follow-up nudges for the worker and mother, active in Rajasthan. "JUST ASK!"/ Khoolke Puchho chatbot for family planning, pregnancy and sexual health. mAI, provides 24/7 chatbot services to provide week-by-week guidance on baby development, diet, and symptom management • **Health literacy & self-care :** DISHA, educate rural families on hygiene, nutrition and immunizations through gamified quizzes. Ria highly advanced AI nutritionist that analyzes Indian meals from photos and provides instant calorie/macro breakdowns. Wysa provides 24/7 empathetic listening to explore thoughts and manage worry, low mood and sleep through self-care exercises. Tele-MANAS is national mental health helpline uses AI triaging to provide immediate self-help tools. **Mass communication with AI-tailoring:** Bhashini uses AI to automatically detect user's dialect and translates messages into their language (36+ languages)

Use Case Grouping	Description	Examples	India Specific Examples (OUTSIDE SEARCH)
AI for Frontline Worker Support & Health Service Delivery	Using AI (genAI assistants, triage algorithms, ML-enhanced decision tools) to support CHWs, nurses, and primary-care providers. These tools improve triage accuracy, referral quality, and continuity of care—especially in rural or distributed systems.	• **CHW & frontline decision support:** Empower CHWs' national AI platform, HEP Assist call-center assistant, PATH's AI knowledge assistant. real-time clinical guidance, consistent triage, improved CHW confidence, and accuracy. • **Telemedicine & remote diagnostics:** Somali AI Telemedicine project, DRRIYA remote triage. Extends clinical expertise to remote populations with automated diagnostic support. • **PHC referral and system coordination,** Afya-Tek digital PHC analytics, PROMPTS triage integration in facilities. Closes the gap between the community and the facility, strengthening the PHC continuum. • **Antibiotic stewardship & clinical protocols** ePOCT+/DYNAMIC pediatric algorithms; Ghana AMR AI prescribing tool. Improves adherence to guidelines and reduces inappropriate antibiotic use.	• **CHW & Frontline Decision Support:** Khushi Baby (CHIP), AI automated flagging for high-risk pregnancies. HealthVaani is voice-based AI knowledge assistant for ASHAs to answer clinical queries in real time. • **Telemedicine & Remote Diagnostics:** **eSanjeevani AI (CDSS),** telemedicine platform with integrated AI that suggests differential diagnoses to doctors. • **Antibiotic Stewardship & Protocols:** **AMRSense**, AI tool that analyzes routine hospital data to track resistance patterns and guide prescribing. AMROrbit Scorcard, Visual AI dashboard for clinicians to compare local resistance with national clinical protocols.
System Intelligence, Planning & Resource Allocation	Using AI to see and steer the health system: forecasting supply needs, mapping gaps, allocating resources, and optimizing logistics. These tools rely on administrative, geospatial, and operational datasets.	• **Population health analytics & decision support:** BroadReach Vantage, Palindrome Data for HIV retention, National Intelligence Centers, E-Health Africa portal. Identifies gaps, segments populations, and supports strategic program decisions. • **Supply chain & logistics optimization:** Afya Intelligence forecasting, Zipline's ML routing for drones. Ensures the availability of commodities and reduces delivery times for vaccines, medications, and blood. • **Vaccination uptake optimization:** ADVISER (Help Mum) allocates transport vouchers, reminders, and supports caregivers at the highest risk of missing vaccinations. • **GeoAI for access & planning:** AI facility-access mapping, malaria risk maps, bilharzia hotspot mapping. Guides on where to build services and where to target interventions. • **Data infrastructure that enables AI:** eGabon national system, CNSD, ScanForm OCR, and national EMRs create interoperable, high-quality data systems essential for scalable AI.	• **Population health analytics & decision support:** IHIP, ICMR Cancer Registry Programme provides population-level data for evidence-based decision-making. • **Supply Chain and logistics optimization:** **CoWIN,** used during COVID-19, gave demand forecasting and dose tracking. Drone deliveries for medical products for hilly regions line Zipline, TechEagle. • **GeoAI for Access & Planning:** IMD MausamGPT, ISRO Bhuvan Geoportal, maps health facilities and informs the Ministry of Health on where to establish new health facilities. • **Data Infrastructure that Enables AI:** ABDM, provides interoperable digital highway for consent-based data mobility across all the hospitals. eSanjeevani, generates a massive, real-time dataset of doctor-patient interactions. IHIP , Replaces weekly paper reports with instant digital pings. AI tools (since 2022) scan IHIP data to detect early warning signals for potential epidemics (e.g., dengue, malaria). eHealth Kerala, a pioneering state-level EMR system that has digitized health records for **over 20 million** citizens in Kerala.

Appendix 4: Tiered Prerequisites for AI Use Cases in Public Health

The matrix's tiered structure distinguishes between prerequisites required to safely initiate a use case, conditions that materially enhance effectiveness and adoption, and governance and system foundations that become critical as AI efforts move from experimentation to sustained, system-wide use. This framing reflects an intentional departure from binary notions of readiness. It recognizes that countries can engage with AI incrementally, while remaining explicit about the system conditions that shape risk, performance, and scalability. The matrix, therefore, serves not as a checklist for "readiness" but as a practical guide for sequencing investments and aligning AI use with public health capacity over time.

In the matrix, prerequisites are organized across three columns:

- **Minimum:** foundational conditions needed to initiate a use case safely and responsibly, even in constrained settings.
- **Accelerators:** system, workforce, or governance elements that substantially improve performance, adoption, and operational efficiency, but are not strictly required at the outset.
- **Scale-critical:** institutional, financial, and governance foundations that become essential as AI applications expand in scope, frequency, and reliance within routine public health systems.

Together, these categories capture both AI applications directly visible to populations and providers and less visible but system-critical uses that strengthen data quality, operational efficiency, and decision-making capacity across the public health system.

Use Case Category	Minimum	Accelerators	Scale-Critical
1. AI-Enhanced Diagnostics and Screening at Scale **(e.g., TB, cancer, COVID, CT/X-ray)**	• Digitized imaging data (X-ray, CT, MRI, ultrasound) • Standardized imaging acquisition protocols and metadata • Availability of labeled datasets reflecting local disease patterns • Basic IT infrastructure for image storage, transfer, and retrieval (e.g., PACS or equivalent) • Clearly defined clinical role for AI as decision support, not autonomous diagnosis • Data protection measures for clinical images	• Locally representative training and validation datasets to reduce bias and performance drift • Interoperability between imaging systems and clinical information systems • Continuous data quality assurance and model updating pipelines • Workforce training for radiologists, clinicians, and technicians on AI-assisted workflows • Performance benchmarking against human readers and clinical outcomes • Clinical guidelines defining when and how AI outputs are acted upon	• National regulatory pathways for AI-assisted diagnostics, including liability clarity • Post-deployment monitoring, audit, and recalibration mechanisms • Government ownership or control over deployment architecture and data pipelines • Long-term financing for computer maintenance, upgrades and support • Institutional capacity to assess bias, safety, and real-world effectiveness • Integration into national referral, quality assurance, and surveillance systems
2. AI 4Surveillance, Pattern Recognition, and Early Warning	• Clearly defined public health decisions or responses linked to alerts • Sustained routine data flows from surveillance systems • Basic integration of core epidemiological data sources	• Integration of multisource data (e.g., epidemiological, environmental, climatic, social) to detect patterns and anomalies earlier than traditional surveillance would • Continuous validation of predictions against observed outcomes to improve accuracy and trust	• Government-owned, interoperable data architecture supporting longitudinal analysis • Long-term financing for hosting, maintenance, and model monitoring • Governance and ethical oversight to manage data quality, bias, privacy, and equity risks

Use Case Category	Minimum	Accelerators	Scale-Critical
3. AI for public communication and behavior change:	• Trusted digital channels (e.g., SMS, WhatsApp, apps) • Clearly defined target behavior and population • Basic consent, privacy, and safeguarding measures	• Localization of language, tone, and cultural context • User segmentation and adaptive personalization • Integration with human support or referral pathways	• Public governance over content standards and safeguards • Regulatory clarity on boundaries of automated health advice • Sustainable financing for moderation, updates, and user support
4. AI for frontline worker support and service delivery:	• Clear role definition (AI supports, human decides) • Defined escalation pathways for uncertainty or low confidence outputs • Device access and minimum connectivity	• Localization for language, clinical context, and practice norms • Integration with supervision, referral, and reporting systems • Continuous user feedback and iterative improvement	• Standardized accountability and decision protocols • Long-term workforce enablement and digital literacy strategies • Ongoing monitoring for bias, safety, and unintended harm
5. System Intelligence, Planning, and Resource Allocation	• Legal or policy basis for cross-sector data use • Minimum viable data linkage approach • Clearly defined policy decisions, the intelligence will inform	• Governance mechanisms for data linkage quality and bias management • Multiagency coordination and shared operating procedures • Explainability of analytic outputs for planning and accountability	• Durable data-sharing agreements and oversight bodies • Safeguards against misuse, surveillance, or exclusion • Institutional capacity to translate insights into funded action
5a. Data Quality Automation & Population-Level Analytics	• Government-defined data standards and coding systems • Access to administrative, surveillance, or registry datasets • Clear analytic objectives and auditability of outputs	• Harmonized metadata and master facility/workforce lists • Feedback loops to data producers to improve upstream quality • Stewardship roles for reviewing and validating automated outputs	• National interoperability frameworks and shared identifiers • Public ownership of data pipelines and analytic logic • Stable financing and institutionalization within routine planning and reporting
5b. Administrative and Workflow Optimization	• Identification of high-volume, rule-based administrative processes • Baseline workflow mapping and performance metrics • Frontline user acceptance and basic digital access	• Integration with existing government systems and platforms • Workflow redesign alongside automation, not automation alone • Training and changing management for staff	• Governance mechanisms to ensure that efficiency gains translate into service improvement • Safeguards against vendor lock-in and opaque automation • Long-term budget lines for system maintenance and support

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