Foundations & *Futures*

Vital Strategies

Reimagining Public Health in the Artificial Intelligence Era Across the Global South

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Acknowledgments

This report reflects a collective effort shaped by the insights, experience, and leadership of a wide range of contributors across regions and institutions. The report was developed by Ugonna (Ofonagoro) Adeosun, Pedro do Carmo Baumgratz de Paula, Ph.D., Dr. Adam Karpati and Dr. Mary-Ann Etiebet. The authors gratefully acknowledge the contributions of colleagues across Vital Strategies, including Nidhi Chaudhary, LM Singh, Ruxana Jina, Lara Tabac, Luis Armando Ocaranza-Ordaz, and William Valdez, whose engagement and support were integral to the development and refinement of this report. We extend our sincere appreciation to the public health leaders, policymakers, researchers, and practitioners who generously contributed their time and expertise through interviews, consultations, and ongoing dialogue. Their perspectives were essential in grounding this report in the realities of public health systems navigating the opportunities and complexities of artificial intelligence. We are grateful to all who contributed to this work, including those who requested not to be individually acknowledged.

The authors also wish to acknowledge the following individuals for their valuable insights and contributions: Dr. Karthik Adapa (Regional Adviser, Digital Health, World Health Organization South-East Asia Regional Office); Dr. Adaeze Chidinma Oreh (then Honourable Commissioner for Health, Rivers State, Nigeria); Dr. Adanna Steinacker (Senior Special Assistant to the President of Nigeria on women's health); Dr. Sa'ed Adel Robin Assaf (Specialist in Community Medicine and Public Health; Head of Mortality and Morbidity Surveillance Department, Ministry of Health, Jordan); Dr. Noor Khader Jodeh Abdulbaqi (Head of Maternal and Perinatal Mortality Department, Ministry of Health, Jordan); Irene Dankwa-Mullan, MD, MPH (CEO and Co-Founder, Protea Global Solutions; Affiliate Professor, Milken Institute School of Public Health, George Washington University); Dr. Benson Droti (Head, Health Information Systems Team, WHO Regional Office for Africa, Brazzaville, Republic of Congo); Lindsey Gottschalk (Vice President, Strategy and Partnerships, data.org); Lic. Juan Edgar Tullo Gómez (Director General, Strategic Health Information, Ministry of Public Health and Social Welfare, Paraguay); Dr. Chikwe Ihekweazu (Executive Director, WHO Health Emergencies Programme); Dr. Satish Khalikar (Digital Health AI Specialist and Program Lead, Wadhwani Institute for Artificial Intelligence); Dr. L. Nneka Mobisson (Co-Founder and CEO, mDoc); Dr. Rose Nakasi (Artificial Intelligence Research Scientist and Lecturer, Makerere University; Head, Makerere AI Health Lab); Dr. Jean Philbert Nsengimana (Chief Digital Advisor, Africa CDC; Dynamik Africa); Raghavendra Rao P.V. (Director, Portfolio, India Health Fund); Karina Rios Michel (Chief Creative and Technology Officer, Girl Effect); Dr. Piyush Singla, IAS (Secretary to the Government, Information Technology Department, Government of Jammu and Kashmir, India); Dr. Mariângela Batista Galvão Simão (Secretary of Health and Environmental Surveillance, Ministry of Health, Brazil); Dr. Muhammed Semakula (Ministry of Health, Rwanda; former Permanent Secretary); Jacob Taylor (Fellow, Center for Sustainable Development, Brookings Institution); Professor Tiago Timponi Torrent, Ph.D. (Professor of Linguistics, Federal University of Juiz de Fora; Head, FrameNet Brasil Computational Linguistics Lab; CNPq); Rafael Zanatta (Executive Director, Data Privacy Brasil Research Association); and Steve Wunker (Managing Director, New Markets Advisors).

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Executive Summary

Artificial intelligence (AI) is reshaping what public health systems can see, understand, and do. Across the Global South, governments are experimenting with how AI can detect risks earlier, allocate resources more effectively, and extend the reach of care. But the central finding of this report is that **the true measure of AI's promise lies in the strength of the foundations beneath it.** AI cannot compensate for weak public health systems. It can only build on what is already institutionally, digitally, and politically in place.

This report draws on three lines of inquiry. **First**, a thematic synthesis of more than two dozen interviews with ministries of health, intergovernmental organizations, implementers and global thought leaders working across Africa, Asia and Latin America. **Second**, with a Foundational Readiness Scan covering 83 countries across Africa, South and Southeast Asia, Latin America and a Middle East sample, drawing on publicly available indicators of AI policy, connectivity, interoperability, health data availability and workforce capacity. **Third,** following a rapid landscape scan of 264 AI-related public health applications, organized into **Use-Case Groupings for Public Health** and informed by consultations, we developed a Prerequisites Matrix that distinguishes the minimum conditions needed to initiate a use case safely, the accelerators that improve performance and adoption, and the scale-critical foundations needed for sustained, systemwide use. Country spotlights from Rwanda, India, Rio de Janeiro, and Recife illustrate what becomes possible when foundations and use cases align.

Across these inputs, AI readiness emerges as system readiness. Two layers of foundations prove decisive:

- **Within the public health system:** foundational data systems that are institutional, digitized, and interoperable; governance and public institutional ownership; human and institutional capacity; and financing models that treat data and digital systems as long-term public infrastructure rather than time-bound projects.
- **Across the wider national ecosystem:** digital public infrastructure and national digital ecosystems; legal, regulatory, and trust architecture; and cross-sector coordination mechanisms that allow shared intelligence to translate into shared public action.

The Foundational Readiness Scan reveals significant variation across regions. Roughly one-third of countries reviewed have adopted a national AI policy that explicitly addresses health. Connectivity remains uneven, with regional average ICT Development Index (IDI) scores ranging from 59 in Africa to 88 in the Middle East sample. Interoperability is partial in most settings, core health data are incomplete in a significant subset of countries, and digital health workforce capacity is thin almost everywhere. These are not secondary technical issues. They are binding constraints on whether AI can be absorbed by public health systems at all. At the same time, *no region holds all the answers*: Some countries are moving faster on policy, others on digital public infrastructure, still others on embedding AI use cases into routine system functions—a pattern that points to South-South learning as an accelerator of progress.

The use-case landscape is already diverse and expanding. Five recurring functional groupings emerged: **AI-enhanced diagnostics and screening**, **surveillance and early warning**, **public communication and behavior change**, **frontline worker support and service delivery**, and **system intelligence, planning, and resource allocation**. The Prerequisites Matrix shows that different use cases depend on different combinations of foundations, but in every case, durable value depends less on the tool itself than on the strength of the surrounding public system. Country spotlights make the same point in practice: Rwanda's Health Intelligence Center built on a national civil registration backbone; India's Ayushman Bharat Digital Mission anchoring AI-enabled decision support across 430 million teleconsultations; Rio de Janeiro's integration of 6.5 million residents into a single analytic environment for outbreak and climate-health response; Recife's use of AI on routine primary-care records to surface previously invisible signals of gender-based violence and suicide risk.

On the basis of this evidence, the report sets out three principles to guide governments, funders and partners. AI adoption in the health sector must be:

- **Guided by strategies for sustainable public health integration**—with financing and workforce capacity that extends beyond initial build to maintenance, integration, and institutionalization.
- **Responsive to local governance structures—**institutionalizing public governance and oversight that protect sovereignty, maintains accountability to the public interest, and earns public trust. Countries cannot govern what they do not control.
- **Advanced with public health data systems that are inclusive and connected—**prioritizing investment in foundational public health data systems and digital public infrastructure as the basis for scalable, equitable health impact.

The future of AI in health will not be determined by technical innovation alone. It will be determined by how well countries are able to integrate AI solutions and tools into local strategy, structures, and foundational systems. Capturing the promise of AI therefore requires a shift in investment focus to prioritize foundational public health systems.

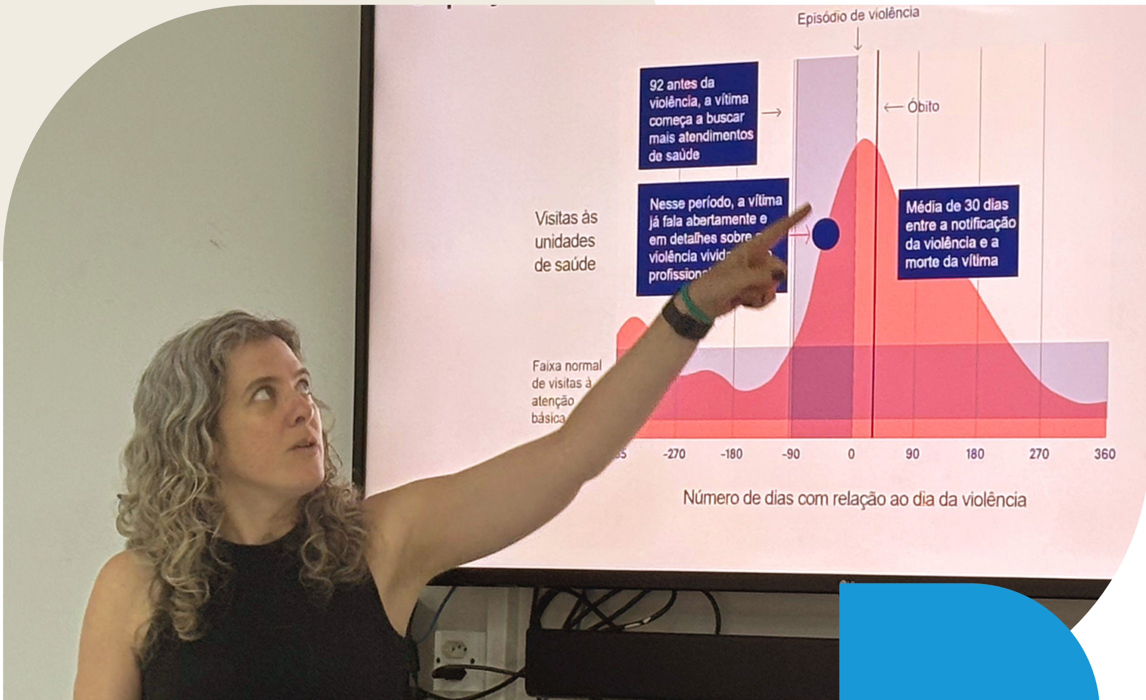
Introduction

Across the globe, artificial intelligence is beginning to reshape what public health systems can see, understand, and do.[1] New tools are expanding the ability of governments and health institutions to detect risks earlier, improve service planning, and engage populations in more tailored ways.[2] They offer the possibility of building stronger public health intelligence: systems that work together to generate timely insight, connect information across sources, support better decisions, and translate data into action in the public interest.[3] AI is advancing quickly, but the public sector systems expected to receive, govern, and use it are not all equally prepared.[4] Where foundational systems remain weak, AI risks adding new layers of fragmentation, opacity, and pilots that never scale, widening health and development gaps within and across countries. Where they are stronger, AI can help public health systems become more proactive, coordinated, and effective.[5]

This tension is especially consequential across the Global South. Countries across Africa, South and Southeast Asia, and Latin America are approaching the AI era from different starting points, with different institutional histories, digital trajectories, and public health priorities.[6] Yet a common strategic question is emerging: What does it take to build public health systems that can use AI in ways that strengthen public value? In some settings, governments are building that capacity through investments in digital public infrastructure, interoperable data systems, public-sector governance, and digitally enabled workforces.[7] In others, innovation is moving faster than the systems needed to receive, govern, connect, and scale it.[8] The result is a widening difference between AI as a source of disparate tools and AI as an integrated public good.

This report is therefore framed around a simple premise: **AI cannot compensate for weak public health systems. It can only build on what is already institutionally, digitally, and politically in place.[9]** High-quality data systems, effective governance, interoperability, inclusive connectivity, and human and institutional capacity are not secondary conditions. They are what determine whether AI can serve public health at all, and whether it can do so equitably, responsibly, and at scale.[10] Without these foundational conditions, even the most promising tools are likely to remain fragmented and confined to pilot programs. With them, countries are better positioned to generate earlier warnings, support frontline decisions, improve service coordination, strengthen planning, and produce better public health outcomes.

Reimagining public health in the AI era is therefore not chiefly a question of technological sophistication. It is a question of state capability, system design, and public purpose. We have found this perspective missing from many of the discussions guiding efforts and investments in this space. A growing body of important work is mapping the implications of AI for health—from the European Union's readiness assessment of AI in health systems under its new AI Act, to analyses of AI governance by the organization for Economic Co-operation and Development (OECD),[11,12] to WHO's ethics and regulatory guidance on artificial intelligence and on large multimodal models. These efforts have largely centered on clinical AI, regulatory architecture, and high-income health systems. Foundations & Futures complements that work by approaching AI from a different vantage point: as a **public health** question rather than primarily a clinical or regulatory one, anchored in the realities of the **Global South**, and oriented toward the foundational systems that determine whether AI can be absorbed at all. As a global public health organization whose mission is to ensure that everyone, everywhere is protected by strong public health systems, we have examined these issues through a public health lens. We hope this report provides readers with new perspectives on the foundational systems required to improve health outcomes at population and community levels, the regional landscapes shaping broader socio-economic and governance factors, the futures that stronger and more responsive systems can unlock, and the practical actions that governments, funders, and partners should prioritize now.



About This Report

This report was shaped through an extensive and iterative process of engagement with practitioners and experts in public health, digital information systems, and artificial intelligence—inside and outside governments—including in-depth interviews and a synthesis of discussions at country, regional, and global levels. These exchanges, spanning Africa, Asia, and Latin America, and including convenings such as the Global Digital Health Forum and the Global Health AI Summit, were central to grounding the analysis in real-world system constraints, policy priorities, and implementation experience. The analysis also draws on publicly available data, frameworks, and global resources, including contributions from the World Health Organization, World Bank, International Telecommunication Union, and other partners working at the intersection of data, digital infrastructure, and health systems strengthening.

The report is organized in five parts:

- **Part I: Stakeholder Interviews**—a thematic synthesis of how ministries of health, multilateral institutions, implementers, and global thought leaders define AI readiness, the foundational conditions they consider necessary, and where they see risks and opportunities for scale.
- **Part II: Foundational Readiness Scan of the Global South**—a directional country-by-country review across 83 countries, drawing on publicly available indicators of AI policy, connectivity, interoperability, health data availability, and health and digital workforce capacity.
- **Part III: Futures: What Intelligent Public Health Systems Can See and Do**—a rapid landscape scan of 264 AI-related public health applications, organized into five recurring functional groupings and a tiered Use-Case Prerequisites Matrix.
- **Part IV: Regional Spotlights**—comparative analysis across Africa, South and Southeast Asia, and Latin America, with country spotlights on Rwanda, India, Rio de Janeiro, and Recife.
- **Part V: Discussion and Framework**—a synthesis that organizes AI readiness as a set of foundational capabilities at two interconnected levels (the public health system and the wider national digital ecosystem), followed by a call to action grounded in three principles for governments, funders, and partners.

Detailed findings, methods, and country-level data are presented in the Appendices.

- **Appendix 1:** Foundations and Futures: Thematic Interview Analysis
  Provides a structured synthesis of key informant interviews and stakeholder consultations. It includes a summary of respondent categories, the analytic approach, and three tables covering current-state findings, insights and recommendations, and governance and legal considerations for AI in public health.

- **Appendix 2:** Foundational AI Readiness by Country
  Presents a directional country-by-country readiness scan across Africa, South and Southeast Asia, Latin America, and the Middle East. The scan uses publicly available indicators on AI policy, connectivity, interoperability, health data availability, health workforce density, and digital health workforce maturity

- **Appendix 3:** Rapid Use-Case Landscape Scan Across the Global South
  Describes the methods and findings from an exploratory scan of AI-related public health applications across Global South regions and selected comparator contexts. It groups identified examples into major functional categories, including diagnostics and screening, surveillance and early warning, public communication and behavior change, frontline worker support, and system intelligence, planning, and resource allocation.

- **Appendix 4:** Tiered Prerequisites for AI Use Cases in Public Health
  Presents the AI Use-Case Prerequisites Matrix developed through consultation and desk review. The matrix organizes public health AI use cases by the minimum conditions needed to initiate them safely, the accelerators that strengthen performance and adoption, and the scale-critical foundations required for sustained systemwide use at scale.

PART I:

Stakeholder Interviews

This section draws on a rapid, cross-case qualitative synthesis of key informant interviews and stakeholder consultations with government representatives, intergovernmental organizations, implementers, funders, and thought leaders working across public health, digital health, data systems, and AI. The interviews examined how different actors define AI readiness in public health, what foundational conditions they consider necessary for responsible adoption, and where they see risks, gaps, and opportunities for scale.

Respondent category	Types of affiliations	Regions represented	Roles/titles	Number of respondents
Government	**Ministries of Health**	Nigeria, Kenya, Cameroon, Paraguay, Jordan, India, Brazil	Technical Advisors; Director of Strategic Information; Director of Policy and Research; Senior Special Assistant, Health Commissioner	12
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; Team Leader /Health Information and Knowledge Management	4
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 & Urban Epidemiologist; President & CEO; Fellow, Global Development; Director	12

Summary of Interview Respondents

Thematic Analysis

We applied a framework-based thematic analysis, organizing insights into four interconnected analytic domains: Critical Building Blocks, Promising Use Cases, Concerns and Risks, and Enablers and Drivers. These domains were defined a priori, through a landscape review and Vital Strategies' prior 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.

Synopsis of Thematic Analysis of Interviews

(see Appendix 1 for full tables of summarized analysis).

Theme	Sub-Theme	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.
Promising Use Cases	**Predictive Analytics & Early Warning Systems**	Predictive models enhance the detection of outbreaks, missed 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 workload and speeding diagnosis. One of the most consistently high-impact use cases was 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, SRH, and refugee data heighten ethical risks, while vendor-controlled infrastructures threaten national sovereignty.
	Data Fragmentation, Poor Quality & Algorithmic Bias	Fragmented, incomplete, or non-representative 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, fears 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.

Theme	Sub-Theme	Summary
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 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.
	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. Co-design and human-in-the-loop approaches strengthen 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 enable governments and communities to retain control over value and decision-making.

Respondent Viewpoints

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, conversations with ministry representatives and nongovernmental experts alike elicited a standard warning:

> ***AI is moving faster*** **than the systems meant to support it.**

Accordingly, respondents across countries described AI readiness not as a single benchmark but as a set of conditions. Below is a summary of respondent viewpoints around the first theme in the table.

Critical Building Blocks

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, a global health leader, 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.

Overall, those working closest to these systems pointed to weak coordination across ministries, unclear mandates, limited institutional ownership of digital systems, and policies that exist on paper without being operationalized through review, monitoring, or audit. One point came through with particular force: Countries cannot govern what they do not control. Where infrastructure, data pipelines, or system design are shaped more heavily by external actors than by public institutions, ministries are left with responsibility but insufficient authority.

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.

Respondents also stressed that pilots are more likely to scale when they are designed from the beginning with national integration in mind. Alignment with local or subnational priorities is important, but not enough. If pilots are not connected to national health policies, national software systems, or broader digital public infrastructure, they risk remaining isolated experiments. As one respondent from a Ministry of Health in the Africa region noted, ***"Pilot fatigue may come, but it can be avoided at the time of initiation phase of these pilots."*** The same respondent emphasized that scale depends on early alignment with national priorities: ***"The alignment should not be only with the state priorities, but with the national priorities also."***

Taken together, these reflections add an important implementation lesson: Sustainability is not only about financing after a pilot ends, but is also about designing pilots with a clear pathway into national systems from the start. Those working closest to implementation were direct: They said that financing is what determines whether AI remains a sequence of promising demonstrations or becomes part of a durable public health capability. Respondents emphasized the need to shift from project financing to infrastructure financing.

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. When data is incomplete, unconnected, or poorly governed, even the most sophisticated models struggle to deliver value.

"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."***

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, an Innovator, 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?

Consistently, respondents reiterated that public health data systems remain fragmented, incomplete, and weakly interoperable in many settings. Surveillance systems, disease registries, health information platforms, facility and workforce registries, administrative records, and civil registration systems often operate in parallel rather than as a connected whole. Respondents described donor-specific platforms duplicating national systems, the absence of shared identifiers, weak registries, inconsistent standards, and limited visibility into rural and marginalized populations. As a Regional Global Health leader put it, ***"Whenever the data is not talking to itself, data is just all over the place."***

Respondents also emphasized that data readiness is not only about volume or completeness. It is also about whether data is operationally fit for purpose. For AI tools to perform reliably, data must reflect the real conditions in which tools will be used, including different devices, care settings, workflows, and user behaviors. One respondent, an African Digital Health Implementer, explained, ***"For you to actually build AI systems that work and perform for the population that it's built for, you need to have the right datasets. You need to be able to have a holistic dataset as a true representation of the people who are going to use this AI."***

This shifts readiness from simply asking whether data exists to asking whether data is representative, validated, interoperable, and usable for the specific decision or workflow the tool is meant to support. As another respondent, a Health Innovation Funder, noted, the real work often lies in ***"pre-processing these data, and getting the quality of data, getting the quality of annotations to make sure it's well***

performing." Without this foundation, weak data systems do not simply limit AI performance; they can also distort it. ***As one global data and AI leader warned, "All of your bad data just becomes bad AI and ensuing decisions."***

Together, these reflections reinforce the broader finding that AI readiness depends on data quality, interoperability, operational fitness, and alignment with national digital infrastructure rather than stand-alone datasets, disconnected platforms, or isolated pilots.

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 Digital Health 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."***

These constraints show that connectivity is more than an access issue. As one global thought leader noted, ***"How do you build robust datasets when you have real constraints in terms of data storage space?"*** For communities that are already the least visible in public health data, these gaps determine whether AI-enabled systems can capture, store, and use information equitably, or whether they reproduce the same exclusions in a more advanced form.

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 will 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 of Health 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.

A government representatives respondent from the South and Southeast Asia consultation added that institutional readiness also depends on leadership intent and change management. Infrastructure and trained human resources are necessary, but not sufficient. Institutions must also be prepared for the operational and cultural shift that occurs when manual systems become digital and performance becomes more visible.

"The most important thing is they should be ready for the change management which is going to happen because of the AI or digital health technology."

They emphasized that digitization creates accountability by making system performance visible:

"They should be ready to face the transparent outcomes which are going to be visible to all through the data or the reports or the dashboards which are going to come out from the use of or non-usage of digital AI solutions."-Digital Health Implementation Expert

Beyond skills and human capacity, AI readiness also requires institutions to be willing to absorb what digital systems reveal, address process gaps, and support staff through changes in roles, workflows, and expectations.

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."-Digital Health Implementer***

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.

Respondents also stressed that pilots are more likely to scale when they are designed from the beginning with national integration in mind. Alignment with local or subnational priorities is important, but not enough. If pilots are not connected to national health policies, national software systems, or broader digital public infrastructure, they risk remaining isolated experiments. As one respondent noted, ***"Pilot fatigue may come, but it can be avoided at a time of initiation phase of these pilots."*** The same respondent emphasized that scale depends on early alignment with national priorities: ***"The alignment should not be only with the state priorities, but with the national priorities also."***

Taken together, these reflections add an important implementation lesson: Sustainability is not only about financing after a pilot ends. It is also about designing pilots with a clear pathway into national systems from the start. Those working closest to implementation were direct that financing is what determines whether AI remains a sequence of promising demonstrations or becomes part of a durable public health capability. Respondents emphasized the need to shift from project financing to infrastructure financing.

PART II

Foundational Readiness Scan of the Global South

To understand how prepared countries across the Global South are to optimize the use of AI in public health, we compiled an AI Foundational Readiness Scan spanning Africa, South and Southeast Asia, Latin America, and the Middle East. The scan is directional rather than diagnostic. It is based entirely on desk review of public sources, including national AI policy trackers, and may therefore lag recent reforms, miss subnational variation, or differ from how governments characterize the current state of their own systems. It brings together five groups of domains that, taken together, help shape foundational AI readiness.

- **AI Policy:** Captures the existence, type, and status of a national AI policy, strategy, framework, or related policy instrument. It also notes how explicitly health is identified as a priority sector or use case, reflecting the degree to which public health is positioned within the national AI agenda.

- **Connectivity:** IDI connectivity score 2025 was used as a proxy for digital infrastructure and access. The score ranges from 0 to 100, with higher scores indicating stronger progress toward universal and meaningful connectivity. It combines 10 indicators across access, use, affordability, traffic, device ownership, and digital skills. It assesses internet penetration, mobile coverage, and basic ICT capacity, which determine whether AI tools that rely on connectivity can function in practice.

- **Interoperability (Digital Health):** An interoperability score drawn from the Global Digital Health Monitor (GDHM) tracks how far countries have progressed in establishing the standards, architecture, and health information exchange mechanisms needed for interoperable digital health systems. The score uses GDHM's five-phase maturity scale, from Phase 1 to Phase 5, with higher scores reflecting more mature, nationally coordinated systems that support routine and standardized datxchange across digital health platforms. GDHM places this measure within its Standards and Interoperability do

- **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 are (mortality, service coverage, risk factors).

- **Workforce (Health Care and Digital Health):** World Bank health care workforce density serves as a proxy for the strength of the clinical workforce. A digital health workforce maturity score uses the GDHM Workforce domain, which averages four indicators: digital health integration into pre-service and in-service training; formal training programs that produce a dedicated digital health workforce; and the maturity of public-sector digital health career paths. The GDHM score uses a five-phase maturity scale, from **Phase 1 to Phase 5**, with higher scores reflecting stronger integration of digital health into pre-service and in-service training, the presence of formal training programs for a dedicated digital health workforce, and more mature public-sector digital health career paths.

Findings and Insights

1. AI policy: Development varied across regions, with the strongest policy coverage observed in the Middle East sample and South/Southeast Asia. All four Middle Eastern countries included in the scan had adopted or approved AI policies, and all four specified health. South/Southeast Asia also showed strong policy coverage, with nine of 13 countries having adopted or approved AI policies, all of which specified health. Africa showed a more distributed pattern. Of the 54 African countries included, 21 had adopted or approved AI policies, 16 had drafted but not passed policies, and 17 had no identified AI policy. Among countries with adopted or approved policies, 20 clearly specified health. Nigeria, Kenya, Ghana, Egypt, Morocco, Rwanda, Zambia, and Zimbabwe were among those with adopted AI policies that specified health. South America showed a mixed pattern, with six of 12 countries having adopted or approved AI policies, two with drafted policies, and four with no identified AI policy.

Region	Countries in scan	Adopted or approved AI policy	Drafted, not passed	No policy	Health specified in AI policy
Africa	54	39%	30%	31%	37%
South America	12	50%	17%	33%	50%
South/Southeast Asia	13	69%	23%	8%	69%
Middle East	4	100%	0%	0%	100%

2. Connectivity: Scores were highest in the Middle East sample, where all four countries had IDI scores of 75 or higher, and two had scores of 85 or higher. Saudi Arabia and Iran were among the strongest performers. South America also showed high connectivity scores, with eight of 10 countries with available data scoring 75 or higher. Chile, Uruguay, Brazil, Argentina, Suriname and Paraguay were among the stronger performers in the region. South/Southeast Asia had an average IDI score of 74, with seven of 11 countries with available data scoring 75 or higher. Thailand, Vietnam, Bhutan, Indonesia, the Maldives, and the Philippines were among the stronger performers. Africa had the lowest regional average, but 11 of 44 countries with available data scored 75 or higher, including Morocco, Libya, Mauritius, Algeria, South Africa, Botswana, Seychelles, and Cabo Verde.

Region	Countries in scan	Countries with IDI Scores	Average IDI score	IDI 75 or higher	IDI 85 or higher
Africa	54	44	59	25%	11%
South America	12	10	80	80%	20%
South/Southeast Asia	13	11	74	64%	27%
Middle East	4	4	88	100%	50%

3. Interoperability and standards integration varied across regions, with average phases ranging from two to three. Africa had the largest number of countries with data, with 39 of 54 countries covered. Six African countries were at phase 4 or higher, and three were at phase 5. Kenya, Malawi, and Tanzania recorded phase 5, while Botswana, Benin, and Guinea recorded phase 4. South/Southeast Asia had complete data across all 13 countries. Two countries, India and the Philippines, were at phase 4 or higher. No country in the South/Southeast Asia group recorded phase 5. In South America, data were available for four of 12 countries; Brazil recorded phase 5. In the Middle East sample, data were available for three of four countries; Saudi Arabia recorded phase 5. South America and the Middle East showed higher proportions of countries at phase 4 or higher, but these estimates were based on smaller data denominators.

Region	Countries in scan	Countries with interoperability data	Average phase	Phase 4 or higher	Phase 5
Africa	54	39	2	15%	8%
South America	12	4	3	25%	25%
South/Southeast Asia	13	13	3	15%	0%
Middle East	4	3	3	33%	33%

4. Health data availability: was highest in the Middle East sample, South America, and South/Southeast Asia. All four Middle Eastern countries included in the scan had health data availability of 80% or higher. South America had 10 of 11 countries with available data above 80%, and four countries at 90% or higher. Uruguay, Chile, Peru, Paraguay, Colombia, Ecuador, Guyana, Suriname, Argentina, and Venezuela were among the countries with health data availability of at least 80%. South/Southeast Asia also showed relatively strong results, with seven of 13 countries at 80% or higher and three at 90% or higher. Sri Lanka, Bangladesh, Bhutan, India, Cambodia, Pakistan, and Thailand were among the countries above the 80% threshold. Africa had complete data for all 54 countries and an average health data availability score of 62%. Eight African countries had scores of 80% or higher, with Egypt, Ethiopia, and Morocco at 90% or higher.

Region	Countries in scan	Countries with data on the availability of recent data to monitor health-related SDGs	Average % availability of recent data to monitor health-related SDGs	Countries with 80% or higher availability of recent data to monitor health-related SDGs	Countries with 90% or higher availability of recent data to monitor health-related SDGs
Africa	54	54	62%	15%	6%
South America	12	11	86%	91%	36%
South/ Southeast Asia	13	13	81%	54%	23%
Middle East	4	4	88%	100%	25%

5. Workforce (Health and Digital Health)

5a. General health workforce capacity: Physician density was highest in the South America and the Middle East samples. All 12 South American countries had at least one physician per 1,000 people, and seven had at least two physicians per 1,000. Argentina, Uruguay, Paraguay, Chile, Colombia, Ecuador, Brazil, and Peru were among the stronger performers. In the Middle East sample, all four countries had at least one physician per 1,000 people, and two had at least two physicians per 1,000. Saudi Arabia and Jordan were among the stronger performers. Africa and South/Southeast Asia had lower physician density overall. In Africa, six of 54 countries had at least one physician per 1,000 people, and two had at least two physicians per 1,000. Seychelles and Libya were the strongest African performers. In South/Southeast Asia, five of 13 countries had at least one physician per 1,000 people, while only one country reached the two physicians per 1,000 threshold.

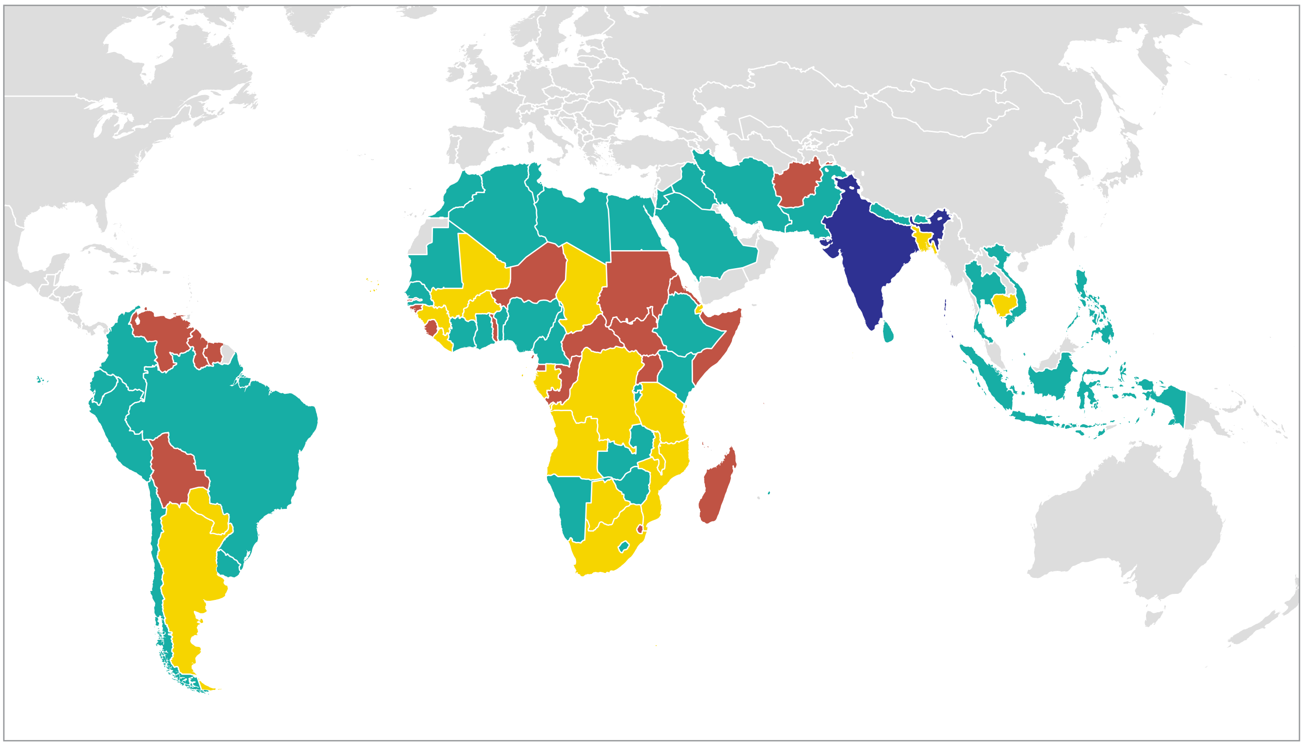
Region	Countries in scan	Countries with physician density data	Average physicians per 1,000 people	Physicians 1 or higher per 1,000	Physicians 2 or higher per 1,000
Africa	54	54	0	11%	4%
South America	12	12	3	100%	58%
South/ Southeast Asia	13	13	1	38%	8%
Middle East	4	4	2	100%	50%

5b. Digital health training integration: varied across regions, with the strongest results observed among the South American countries with available data. All four South American countries with data were at phase 3 or higher, and two were at phase 4 or higher. Brazil and Argentina were among the strongest performers. However, data were available for only four of 12 South American countries, so this regional pattern should be interpreted cautiously. South/Southeast Asia had broader data coverage, with 12 of 13 countries represented. Seven countries scored phase 3 or higher, while one country scored phase 4 or higher. Thailand had the strongest score in the region, while Indonesia, Sri Lanka, Bangladesh, Nepal, Vietnam, and the Philippines were among those at phase 3. In Africa, 39 of 54 countries had data. Twelve countries scored phase 3 or higher, and three scored phase 4 or higher. Ethiopia had the highest score in the region, followed by Malawi and Guinea. Ghana, Liberia, Mali, Egypt, Rwanda, Zimbabwe, and Uganda also showed moderate levels of integration. In the Middle East sample, Saudi Arabia recorded the highest score.

Region	Countries in scan	Countries with digital health training data	Average phase	Phase 3 or higher	Phase 4 or higher
Africa	54	39	2	31%	8%
South America	12	4	4	100%	50%
South/Southeast Asia	13	12	2	58%	8%
Middle East	4	3	3	67%	33%

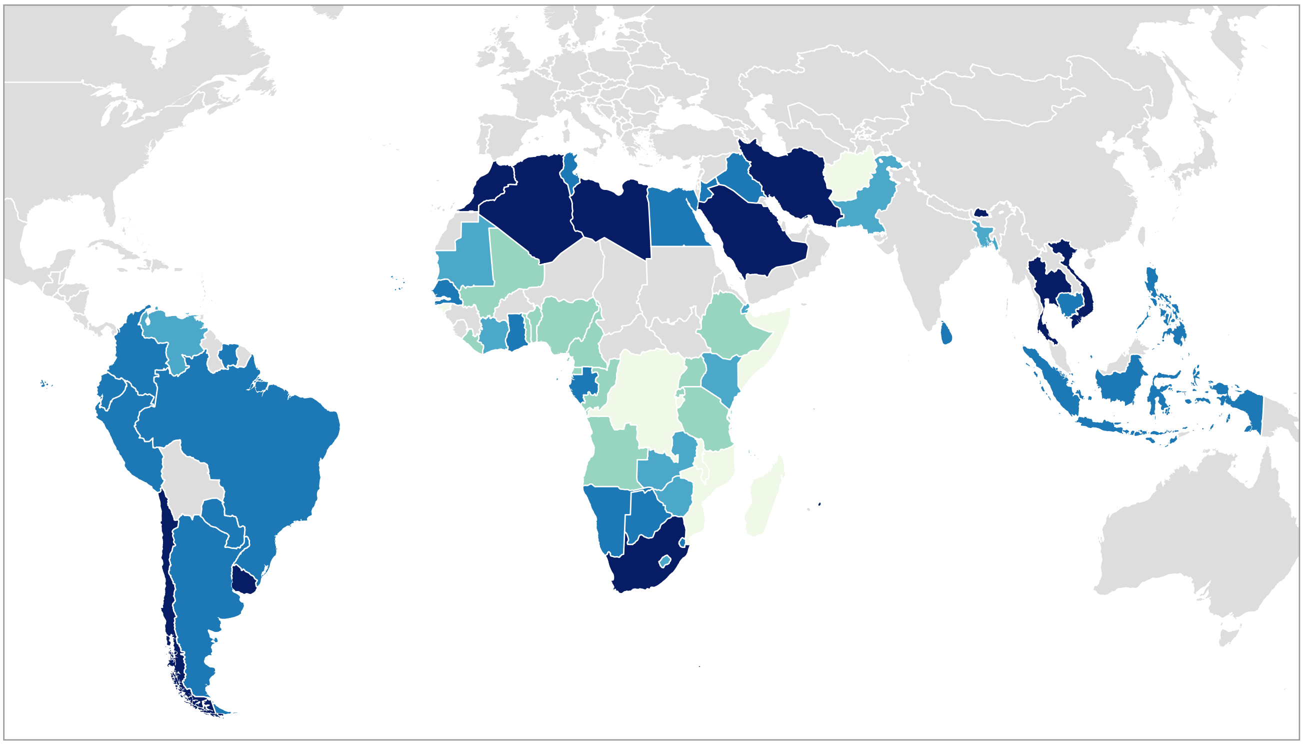
The scan shows a consistent pattern: Policy intent is emerging faster than systems. Roughly one-third of countries have adopted an AI policy, but digital connectivity remains uneven, interoperability is partial in many settings, core health data are incomplete in a significant subset of countries, and 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.

National AI Policy/Strategy Adopted or Approved



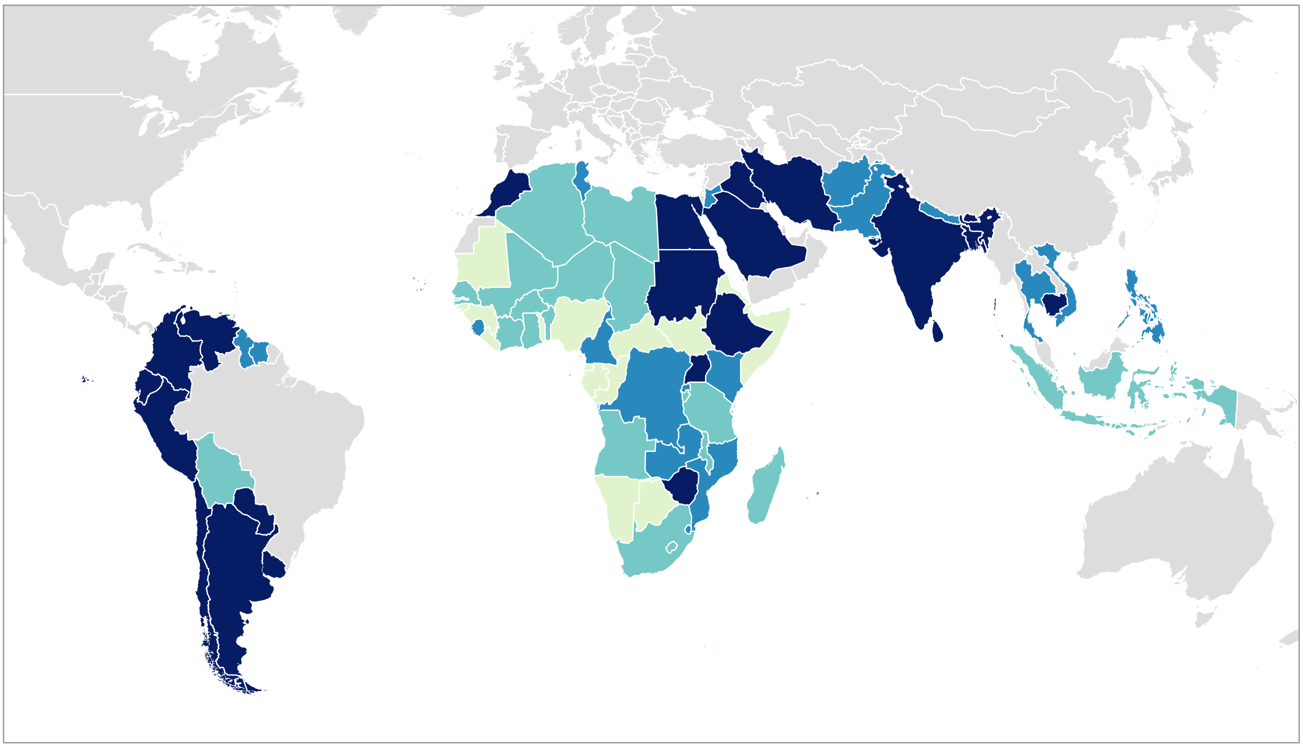
No | Draft | Yes | Yes (Dedicated AI Strategy for Health) | Not included/no data

Connectivity - IDI Score 2025



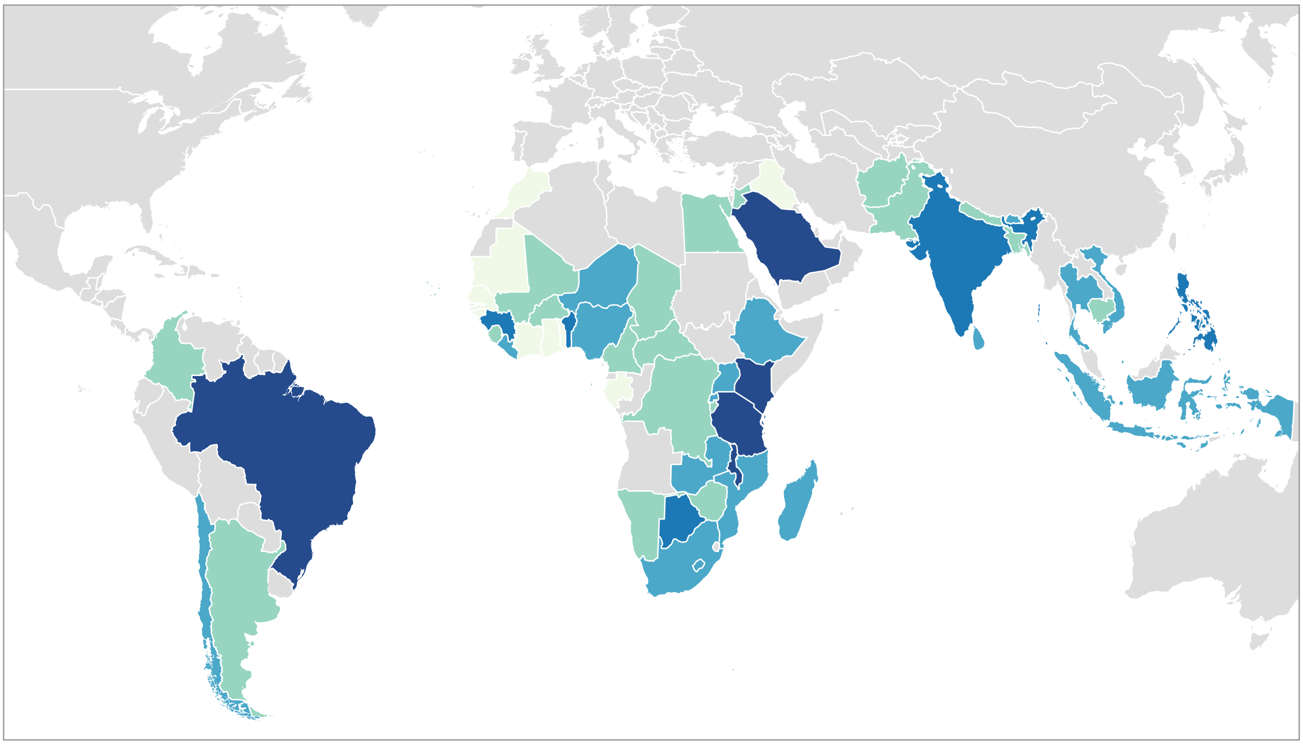
‹40 | 40-55 | 55-70 | 70-85 | ≥85 | Not included/no data

Health Data - WHO SCORE
Availability of latest data to monitor the health-related SDGs

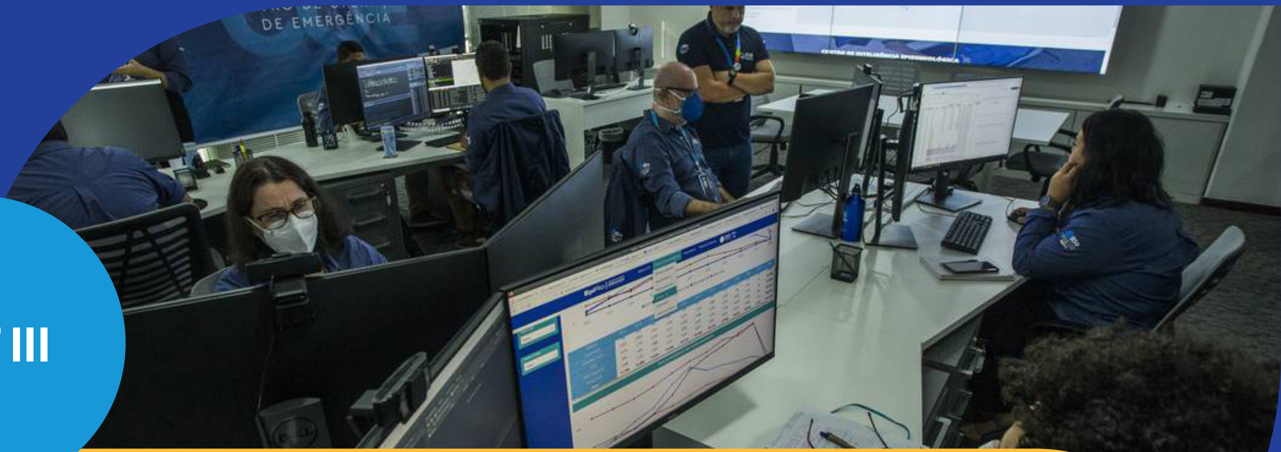


‹55 55-70 70-85 ≥85 Not included/no data

Interoperability Phase (1-5)



Phase 1 2 3 4 5 Not included/no data



PART III

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.[13] 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.[14] 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 with persistently low vaccination coverage, or combining biometric trends and service-use data to identify populations at heightened risk of malnutrition.[15,16]

Enhanced public health intelligence is also reshaping how disease is detected and managed in everyday care, with clear equity implications.[17] **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.[18] 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.[19]

For individuals and communities, AI applications can support **how they receive information and navigate systems.** 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. These systems can operate in local languages, recognize spelling and slang, and adapt content to age, gender, and 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 rooted in trusted digital identities and protected data. For frontline workers, public health intelligence appears as **embedded, practical support.**[22]

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. 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.[24]

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 use that information to design more precise, equitable responses.[25]

Rapid Use-Case Regional Landscape Scan Across the Global South

Searches were carried out by sub-region 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 360 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, 264 examples remained. A qualitative synthesis of these examples identified five recurring functional groupings:

1. **AI-enhanced diagnostics and screening at scale**: Use of machine learning, computer vision, and related methods to analyze clinical images, signals, laboratory outputs, or screening data to support earlier and more accurate disease detection.

2. **AI for surveillance and early warning**: Use of 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.

3. **AI for public communication and behavior change**: Use of generative AI, natural language processing, and personalization algorithms to deliver targeted, culturally responsive health information and support behavior change through digital communication channels.

4. **AI for frontline worker support and service delivery**: Use of decision-support algorithms, triage systems, workflow assistants, and knowledge tools embedded in digitized care environments to support community health workers, nurses, and clinicians.

5. **AI for system intelligence, planning, and resource allocation**: Use of AI on administrative, epidemiological, geospatial, and service-delivery data to generate population-level insights for policy, budgeting, logistics, and strategic planning.
   5a. Data quality automation and population-level analytics: Use of AI to clean, structure, classify, deduplicate, and harmonize large administrative and registry datasets to improve the reliability and usability of data pipelines.
   5b. Administrative and workflow optimization: Use of AI to streamline high-volume, rule-based operational processes in health systems, including scheduling, documentation, claims review, routing inquiries, and supply logistics.

Use-Case Prerequisites

Using the above use-case groupings, we developed a prerequisites matrix to examine the system conditions under which artificial intelligence can 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 cataloguing 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 stand-alone or experimental innovation.

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

AI-enhanced diagnostics and screening: The core dependencies are foundational as much as technical. At a minimum, these use cases depend on digitized imaging workflows, standardized protocols, local datasets, and a clearly defined human role for AI as decision support. As they move toward scale, the requirements broaden to include interoperability with clinical systems, workforce training, regulatory oversight, liability clarity, ongoing recalibration, and long-term financing. In practice, this means that even well-developed diagnostic tools will struggle to generate durable public value unless they are embedded in functioning clinical and regulatory systems.

AI for surveillance, pattern recognition, and early warning: The essential dependencies are routine data flows, basic integration of core epidemiological sources, and the institutional capacity to interpret alerts and connect them to response. As these systems strengthen, they depend increasingly on multi-source analysis, stronger interoperability, continuous validation, and clearer pathways for coordinated public action. At scale, the decisive issue is not simply whether a system can generate an alert, but also whether governments have the governance, financing, and cross-sector coordination needed to act on it.

AI for public communication and behavior change: The starting requirements are different but equally important: trusted digital channels, clear target populations, and basic consent and safeguarding measures. As these tools mature, localization becomes central, including language, tone, cultural context, personalization, and links to human support. At scale, they depend on public governance over content, regulatory clarity, sustainable support, and institutional capacity to monitor trust, harm, and effectiveness over time.

AI for frontline worker support and service delivery: The matrix points first to role clarity, escalation pathways, device access, and minimum connectivity. As these applications evolve, they require closer fit with routine practice through localization, supervision, referral integration, and iterative user feedback. At scale, the key dependencies become workforce enablement, accountability protocols, bias monitoring, and sustained support for adoption and improvement.

System intelligence, planning, and resource allocation: These are more institutionally demanding from the outset. They require, at minimum, a legal basis for data use, some capacity for data linkage, and clarity about which decisions the intelligence is meant to inform. As they mature, they depend on stronger governance for linkage quality, multi-agency coordination, and explainability; at scale, they require durable data-sharing arrangements, safeguards against misuse, institutional capacity to translate insight into funded action, and long-term support for planning and budgeting.

The two subcategories reinforce the same broader lesson. Data quality automation and population-level analytics depend on clear analytic objectives, auditable outputs, data standards, and access to administrative or registry datasets, then evolve toward harmonized metadata, public ownership of data pipelines, interoperability frameworks, and stable financing. Administrative and workflow optimization begins with basic digital access, staff acceptance, and a clear understanding of which repetitive processes are being improved, but at scale it depends on workflow redesign, governance safeguards, and long-term maintenance and support.

Taken together, these patterns underline a central finding of the report: Different AI use cases depend on different combinations of foundations, but in every case, durable value depends less on the tool itself than on the strength of the surrounding public system.

The full tiered Prerequisites Matrix for AI Use Cases in Public Health is presented in the Appendix.

PART IV

Regional Spotlights

The Global South is not entering the AI era from a common starting point. Across Africa, South and Southeast Asia, and Latin America, countries are moving with different institutional histories, digital trajectories, public-sector capacities, and policy traditions. These differences are a source of learning. Across regions, governments are confronting related questions about how to govern AI, strengthen foundational systems, and translate digital momentum into durable public capability. Where distinct strengths emerge and where common constraints persist, countries and regions can learn from one another as they build the foundations of public health intelligence.

Across the evidence reviewed for this report, variation is most visible in four areas: the maturity of policy and governance frameworks, the strength of foundational data and digital systems, the depth of workforce and institutional capacity, and the extent to which countries are able to convert digital activity into durable public capability. These differences matter because they shape not only what kinds of AI applications are currently plausible, but also whether those applications are likely to become part of routine public health practice or remain isolated pilots. At the same time, the interviews and broader synthesis suggest that no region holds all the answers. Some appear to be moving faster on policy, others on digital public infrastructure, others on embedding use cases into real system functions.

Africa

Across Africa, interest in AI for public health is advancing quickly, but foundational readiness remains uneven. The region is seeing growing policy attention, a widening field of pilots and use cases, and stronger recognition of the potential of AI to support diagnostics, surveillance, frontline delivery, and planning. At the same time, many of the conditions required for sustained adoption remain inconsistent across countries, including interoperable data systems, reliable digital infrastructure, workforce capacity, and operational governance. Africa Center for Disease Control's digital transformation strategy frames the challenge on the continent clearly, identifying digital transformation as a major opportunity for African health systems while also pointing to the persistent constraints of inadequate infrastructure and insufficient funding.[26]

Countries such as Rwanda and Kenya show what becomes possible when stronger public architecture begins to take shape, whether through deliberate investment in foundational digital and data systems or stronger institutional coordination for digital health.[27,28] Countries including Nigeria, Senegal, Ghana, and Zambia are beginning to strengthen their connectivity. For example, Zambia's Digital Zambia Acceleration Project is part of the World Bank-supported **Inclusive Digitalization in Eastern and Southern Africa Multiphase Programmatic Approach (IDEA MPA)**, linking Zambia's national broadband, digital ID, secure data platforms, and digital skills agenda to a wider Eastern and Southern African digital transformation pathway that also includes Angola, the Democratic Republic of Congo, Malawi, and the **Common Market for Eastern and Southern Africa (COMESA).**[28]

Africa also highlights something of growing importance for the wider Global South: the practical value of South-South learning. The Africa CDC report's thematic synthesis identifies regional collaboration, partnerships, and embedded talent as important enablers of scale, suggesting that peer exchange can help countries build capacity, strengthen local ownership, and move more effectively from pilots to institutionalization. This aligns with wider work on AI in health, which increasingly points to collaboration, capacity building, and collective learning as core conditions for responsible scale.[30]

SPOTLIGHT 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 foundational 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.[31,32.] 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.[33] 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.[34]

The NCI-CRVS is now operational across health facilities, local cells, and embassies abroad, producing continuous data flows.[35] 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. 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 District Health Information Software 2 (DHIS2), electronic medical records, logistics and supply-chain tools, emergency services, community reporting systems, and major surveys using a six-layer architecture. It starts at the source layer, where systems such as DHIS2; electronic medical records, including eBuzima and the Rwanda Clinical Electronic Medical Record (cEMR); CRVS; the electronic Logistics Management Information System (eLMIS); WelTel; Emergency Medical Services; and the Health Workforce Management System (HWMS) 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 inputs 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)[36] 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 on fragmented project databases.

South and Southeast Asia

Across South and Southeast Asia, the regional picture is shaped by progress in digital health and also by uneven readiness beneath it. Many countries in the region have moved visibly on national digital health planning, digital public infrastructure, and, in some cases, AI policy.[37] At the same time, the region continues to face fragmented and siloed health information systems, limited interoperability, lock-in technology, and inadequate scalable digital infrastructure.

That unevenness is reflected in the different pathways countries are taking. India has built one of the region's most explicit health digital public infrastructure efforts through the Ayushman Bharat Digital Mission, which aims to create an integrated, open, interoperable, standards-based digital health backbone.[39] Indonesia's SATUSEHAT platform is similarly structured as a national health information exchange, and its documentation makes clear that it is responding to a fragmented ecosystem in which hundreds of health applications were not integrated and interoperability standards were inconsistent.[40] Across the region, then, progress is real, but it is often taking place against a backdrop of legacy fragmentation that still has to be resolved.

What stands out in South and Southeast Asia is the difficulty of making scale coherent. As digital systems expand, the central issues become how to connect them across legacy environments, align them across levels of government, and govern them in ways that keep them usable in routine public health practice.[41] In that sense, the region's experience is instructive not because it offers a finished model, but because it makes visible the operational and institutional work required once digital foundations begin to take shape.

SPOTLIGHT 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.[42,43] 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 that can be securely linked, accessed, and shared across settings only when the individual authorizes it.[44] 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.[45]

AI-enabled frontline support and service delivery: eSanjeevani

The national telemedicine platform eSanjeevani illustrates how digital foundations can power AI for frontline worker support and service delivery 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. Through 2025, the platform had facilitated more than 43 crore (430 million) teleconsultations across all 28 states and eight Union Territories.[46] Data captured during these interactions are 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.[47]

COVID Vaccine Intelligence Network (CoWIN), as system intelligence and 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 are trusted and reusable.[48] In the context of the pandemic, CoWIN exemplified AI for system intelligence, policy and planning by providing real-time visibility into vaccine supply, uptake, coverage, and demographic patterns across regions.[49] 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.[50] 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.[51] CoWIN's success is reflected in its scale: 950 million citizens are registered, and over 1.6 billion vaccine doses have been administered and recorded. Through assisted registration, coverage in hard-to-reach tribal communities surpassed the national average, demonstrating the platform's contribution to health equity.[52]

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.[53]

Latin America

Across Latin America, the challenge is no longer simply to introduce digital systems into public health. In much of the region, that shift is already underway. The harder task now is making those systems interoperable, equitable, secure, and institutionally coherent. Latin America is further along in the work of connectivity, digital public goods, standard-setting, and integration with wider public architecture, even if progress remains uneven across countries. Pan American Health Organization PAHO's regional roadmap and progress reporting make this clear: The digital transformation of health in the Americas is already being pursued as a strategic public-sector agenda, not as a set of isolated pilots.

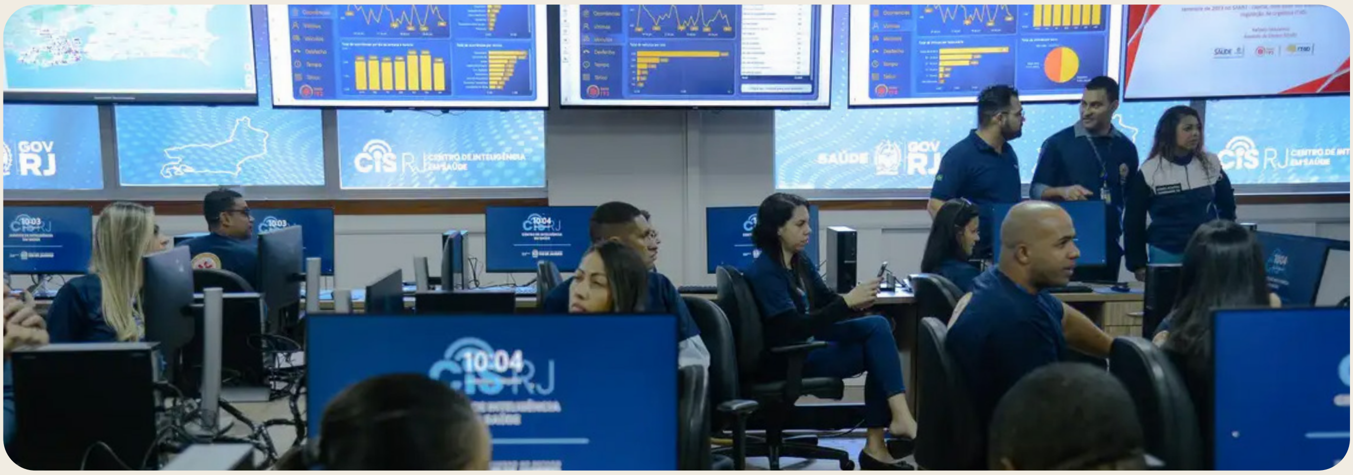
Countries across the Americas are strengthening connectivity and bandwidth, often to expand telehealth and improve access at the first level of care. They are advancing digital public goods, semantic interoperability, standardization, and cross-border data exchange. There is also explicit regional attention to data equity, legal review, human rights, and cybersecurity.

Latin America offers other parts of the Global South a useful lesson in what comes after digital ambition. Once systems begin to exist, the real challenge becomes making them work together: connecting platforms across institutions, governing access and secondary use, strengthening workforce capability, protecting rights, and ensuring that better intelligence actually leads to more legitimate and equitable public action. The region also shows that workforce readiness cannot be treated as secondary. PAHO has increasingly emphasized digital literacy as part of the transformation itself, not as an add-on.

SPOTLIGHT 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 across national and municipal systems holding millions of records 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.[54] Automated pipelines now continuously extract, clean, harmonize, and link records, creating a longitudinal digital cohort of over 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.[55] 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 to check on older adults, children, and bedridden patients.[56] Tested during the 2025 pre-Carnival period, this approach allowed Rio to keep its signature celebrations while reducing avoidable health risks.



SPOTLIGHT 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.[57] Tragically, signals of risk are typically missed and cases become known only when women and adolescents appear in emergency rooms, are hospitalized, or die. 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 a 44% increase in detected risk compared with conventional reporting, representing thousands of cases.

It is also estimated that 13% (around 80,000) of women who accessed primary care in the city 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.

PART V

Foundations and Futures for AI in Public Health

DISCUSSION AND FRAMEWORK

A consistent pattern emerged across the inputs to this Report (consultation findings, readiness scan results, and real-world examples): Interest in AI is advancing faster than the readiness of public health systems to govern, integrate, and use it effectively. Respondents pointed to fragmented and analog data systems, weak interoperability, limited public-sector ownership of digital systems, and governance arrangements that remain underdeveloped for the demands AI places on public health institutions.

A framework for AI readiness emerged as a set of foundational capabilities operating at two interconnected levels. The first sits within the public health system, and the second reflects the wider national digital ecosystem. Within each domain, we provide country examples of exemplary practice.

Public Health Foundations

Our analysis is based on four themes within a country's public health system. Together, these themes describe the conditions that shape whether health information can be generated, connected, governed, and used in routine public health practice:

1. **Foundational public health data systems: institutional, digitized, and interoperable**
2. **Governance and public institutional ownership**
3. **Human and institutional capacity**
4. **Financing and institutionalization**

Foundational public health data systems:

Foundational public health data systems are government-led, population-relevant systems that enable health information to be generated, linked, governed, and used over time. They include surveillance systems, disease registries, health information platforms, civil registration and vital statistics, facility and workforce registries, administrative records, and the interoperability arrangements that allow these systems to function as a connected whole. Digitization of these systems is essential to maximizing their value for AI interventions. They should be able to produce data that are reliable, continuous, and usable for public action. Before algorithms, models, or dashboards can strengthen public health, there must be a core data architecture capable of capturing how populations experience health and disease over time.

From a health equity perspective, interoperability is not only a matter 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 in our consultations 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 that strengthens, not stratifies, public health outcomes.

Exemplars:
Kenya and Paraguay: Kenya's eCHIS provides a national community health data layer that digitizes community-level data collection and use, with Amref piloting an AI-powered Community Health Assistant Reporting Assistant on top of eCHIS in Machakos County. Paraguay's surveillance work uses ETL processes, dashboards linked to official databases, national system integration, and EIOS-supported signal prioritization.

Governance and public institutional ownership

Governance determines whether AI in public health functions as a matter of public strategy or remains a collection of loosely governed experiments. In the AI era, that means whether public institutions have the authority, coordination, and oversight capacity to shape how AI tools are selected, deployed, monitored, and held accountable. It includes stewardship of standards, procurement, access, audit, and the institutional rules that keep digital systems aligned with national priorities and the public interest. Across the Global South, the policy landscape remains uneven. In many countries, no national AI strategy exists. In others, strategies have been adopted but do not speak directly to health, or reference it only in broad terms. Even where health is named, this rarely translates into sector-specific governance arrangements, institutional review processes, model oversight, enforcement mechanisms, or clear accountability for deployment. Interest in AI is advancing faster than the institutional arrangements needed to govern it.

What is needed is a shift from policy declaration to governance operationalization, clearer health-sector mandates, enforceable oversight of data access and secondary use, mechanisms for model review and audit, and procurement leverage that protects public authority over the systems AI depends on. Governance must also be anticipatory rather than reactive—capable of identifying risks early, adapting as systems evolve, and keeping AI accountable to public health goals over time.

Exemplars:
India: The Strategy for Artificial Intelligence in Healthcare for India (SAHI) provides a health-specific artificial intelligence strategy, giving India a national framework for how AI should serve public health responsibly, safely, and at scale. The Indian Council of Medical Research (ICMR) artificial intelligence ethics guidelines add a health-specific framework for ethical decision-making during the development, deployment, and adoption of medical AI tools.

Kenya: Digital Health Act establishes the Digital Health Agency and gives it responsibility for the Comprehensive Integrated Health Information System.

Brazil: The Secretariat of Information and Digital Health (SEIDIGI) gives digital health transformation an institutional home inside the Ministry of Health and coordinates digital transformation within the Unified Health System (SUS).

Human and institutional capacity

Human and institutional capacity determine whether AI strengthens public health judgment or supplants it. Across much of the Global South, this capacity remains limited. Health workforce density is low, and digital health workforce maturity is thinner still. Even where policy ambition and digital infrastructure are advancing, the technical and operational capacity needed to sustain AI adoption often lags behind. Practitioners and policymakers described limited AI and machine learning expertise within ministries, low digital literacy across the health workforce, and continued reliance on paper-based routines in many settings. Too few public institutions are equipped to evaluate AI proposals, monitor performance, or govern implementation with confidence. The challenge is not only whether tools are available, but also whether systems are capable of using them well.

On this, those interviewed were unequivocal: AI does not replace judgment but rather, depends on it. Public health systems still require people who can interpret outputs in context, question whether they make sense, and determine when and how action should follow. Human judgment is not a safeguard against AI; it is part of the system's capability that makes public health intelligence possible. As such, trust emerged as an equally important dimension. Health workers and ministry staff spoke of fears that AI may displace workers, weaken judgment, or introduce unaccountable forms of decision-making. These concerns echo earlier responses to digital systems, where unfamiliar tools were experienced as disruption rather than support. But this is also a design question. Systems that fail to reflect local language, routines, device realities, and patterns of use are less likely to earn trust or translate intelligence into action. Stronger capabilities are needed: A workforce able to use and question AI, institutions able to govern and improve it, and digital systems built for the contexts in which people actually work.

Exemplars:

Thailand: Thailand's digital health agenda links national digital health expansion to workforce capability, with the Ministry of Public Health (MOPH) Digital Health Platform designed to ease workloads and integrate data across service units, and MOPH Academy providing a public-sector training channel for health workers.

Sri Lanka: Sri Lanka shows how human capacity can be institutionalized for digital health: its National Digital Health Blueprint identifies health informatics as a medical specialty that has accelerated digital transformation, while postgraduate informatics training builds local expertise to support digital health implementation across the health system.

South Africa: MomConnect shows institutional capacity to operate a scaled public health communication platform, providing maternal health messaging through SMS or WhatsApp, with chatbot and helpdesk support and nearly 5 million mothers registered across more than 95% of public health facilities.

Financing and institutionalization

Time and again, across every region examined for this report, the same message surfaced: Readiness requires stable, long-term financing that treats data and digital systems as public infrastructure, not as innovations or temporary projects. Donor-funded pilots can generate visibility and short-term value, but many stall before systemic deployment because ministries lack the resources to maintain, integrate, and expand them. Moreover, the financing problem is not only one of scarcity. It is also one of the misallocations. Too much funding goes to the visible technology. Too little goes to the architecture that allows it to endure maintenance, connectivity, hosting, integration, workforce support, and long-term system management. The result is repeated spending on prototypes and externally sustained platforms that struggle to survive beyond the life of a project.

When foundational systems are financed as shared public architecture, the dynamic shifts. Later innovations, whether developed domestically or introduced by external partners, can plug into existing systems rather than rebuilding from scratch. That lowers transaction costs, reduces duplication, and makes future innovation easier to govern, absorb, and scale.

Exemplars:
Brazil: The country's Artificial Intelligence Plan 2024–2028 commits R$23 billion over four years, with an emphasis on public-sector AI and quality-of-life improvements, while SEIDIGI and SUS Digital provide health-sector institutional channels for digital transformation.

National Foundations

The promise of AI for public health also depends on the wider digital, legal, infrastructural, and governance environment that allows health systems to connect with other public systems and operate as part of a broader public architecture. These wider foundations shape whether public health intelligence can move beyond the health sector alone and support more connected, scalable, and durable forms of action. Across our consultations and reviews, three external dimensions emerged as especially decisive: digital public infrastructure and national digital ecosystems; legal, regulatory, and trust architecture; and cross-sector coordination for public action.

1. Digital public infrastructure: national digital ecosystems
2. Legal, regulatory, and trust architecture
3. Cross-sector coordination and public action

Digital Public Infrastructure and National Digital Ecosystems

Digital public infrastructure shapes whether public health intelligence can connect beyond the health sector and function as part of a broader public architecture. It includes the shared national systems and standards that make trusted digital interaction possible across society: identity systems, digital financial exchange capabilities, and data exchange layers. For health systems, these foundations matter because they reduce fragmentation and allow intelligence to move across services, sectors, and levels of government rather than remaining trapped within isolated platforms.

But health systems are not only users of these wider digital foundations. They also help build them. Through birth and death registration, facility records, workforce registries, and other routine public systems, health institutions contribute to some of the most foundational records a state possesses. These systems do more than support service delivery. They help establish who is visible to the state, where health risks are emerging, and how populations can be counted, reached, and served over time. In that sense, health contributes directly to the strength of the national digital ecosystem, even as it depends on that ecosystem to connect, scale, and function well.

Weak connectivity, unreliable power, and limited computing environments still constrain what public systems can see, connect, and act on. This is most visible in primary care, where frontline facilities are expected to support detection, continuity, and population visibility but often lack the digital conditions needed for timely data use. Where facilities cannot reliably upload data or access tools, the gap is not only technical; it also determines whose health needs become visible to the wider system. WHO notes that close to 1 billion people in low- and lower-middle-income countries are served by health facilities with unreliable or no electricity access.

Exemplars:
Thailand: Thailand's MOPH Digital Health Platform connects more than 10,000 service units to a national personal health records system covering more than 64.7 million patients, with more than 1 million electronic referrals and nearly 1.7 million radiographic images processed through linked digital systems.

India and Indonesia: India's ABDM provides a national digital health backbone for integrated health infrastructure, ABHA-linked records, and health facility registries. Indonesia's SATUSEHAT integrates patient medical-record data across hospitals, clinics, laboratories, and pharmacies.

Legal, Regulatory, and Trust Architecture

Legal, regulatory, and trust architecture determine whether public health intelligence can connect across systems without becoming unsafe, extractive, or illegitimate. In the AI era, this architecture is part of the enabling environment that makes data sharing, digital coordination, and AI use acceptable in practice. It includes the rules, institutions, and safeguards that shape privacy, consent, secondary use, accountability, audit, and redress. Where these are clear and enforceable, they create the conditions under which data can move, systems can connect, and public institutions can use intelligence responsibly. Where they are weak, uncertainty and risk multiply quickly.

In many settings, digital health policies exist, but AI-specific governance remains early, fragmented, or weakly operationalized. Review processes, model monitoring, compliance mechanisms, and clear lines of accountability are often missing or underdeveloped. These gaps matter even more because one of AI's strongest public-value promises lies in linking data across health, education, social protection, and demographic systems to support more targeted and equitable action. But the ability to generate that kind of cross-sector intelligence depends on more than interoperability. It depends on trust architecture strong enough to govern who can access data, for what purpose, and under what safeguards. Trust in AI-enabled public health will depend not only on what systems can do, but also on whether people and institutions have reason to believe that those systems are governed fairly, transparently, and in the public interest.

Exemplars:
India and Brazil: India's Indian Council of Medical Research (ICMR) guidelines provide a health-specific ethical framework for medical AI development, deployment, and adoption. Brazil's National Health Data Network (RNDS) links national health-data interoperability with privacy and data protection under the General Personal Data Protection Law (LGPD).

Cross-Sector Coordination and Public Action

Cross-sector coordination determines whether public health intelligence can be translated into a timely, joined-up response across the state. This matters because many of the risks public health systems are expected to detect and address do not sit neatly within the health sector alone. Respondents highlighted the value of linking signals across sectors to identify populations at risk, understand overlapping vulnerabilities, and intervene earlier. But they also pointed to a harder reality: Even where relevant information exists, mandates, incentives, and response pathways often remain fragmented. Public institutions may each see part of the problem, while no part of the state is fully positioned to respond to it in a coordinated way. AI may help reveal patterns more quickly, but it cannot by itself resolve the institutional fragmentation that prevents those patterns from becoming action.

Cross-sector readiness is not only a matter of data-sharing; it is also an issue of state capability. Stronger coordination requires institutional pathways through which shared intelligence can trigger shared action: clear mandates, lawful arrangements for data use, defined response responsibilities, and coordination mechanisms that allow public institutions to act together on risks that no single sector can address alone.

Exemplars:
Nigeria: SORMAS shows how a digital surveillance platform can create the shared workflows needed for AI-ready public action. Operated nationally by NCDC, it supports real-time case reporting, contact tracing, laboratory linkage, outbreak analysis, and coordination across health officers, laboratories, local/state response teams, and national authorities. During COVID-19, its modular design allowed Nigeria to rapidly adapt the system for pandemic response, turning surveillance data into coordinated action across the outbreak-response chain.

Philippines: The Feasibility Analysis of Syndromic Surveillance using Spatio-Temporal Epidemiological Modeler for Early Detection of Diseases (FASSSTER) platform uses surveillance data, electronic medical records, and short message service (SMS) reports to support outbreak forecasting and decision-making.

Call to Action for AI-Ready Public Health Systems

This report highlights a critical principle that is not always emphasized in the norm-setting, decision-making, and resourcing discussions that are shaping the value of AI for public health: High-quality, trustworthy, and publicly governed, 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 dashboards, there must be public systems that can accurately capture how populations experience health and disease over time, govern that information responsibly, and translate it into action.

The findings highlighted 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 high quality and effective public health intelligence possible.

Drawing on this evidence, three principles provide a clear path forward for governments, funders, and partners. AI adoption across the health sector must be:

Guided by strategies to support sustainable public health integration:	**Responsible to local governance structures:**	**Advanced with public health data systems that are inclusive and connected.**
Ensure financing and workforce capacity, not just for initial investments but also for continued maintenance.	Institutionalize public governance and oversight that protects sovereignty, serves and maintains accountability to the public interest, and builds public trust.	Prioritize investment in foundational public health data systems and digital public infrastructure for scalable and equitable health impact.

Strategies for Sustainable Public Health Integration

Sustainability emerged as one of the most consistent themes across conversations. Governments stressed that AI adoption in the health sector must be guided by strategies to support sustainable public health integration. AI readiness cannot depend on short-term pilots, isolated platforms, or donor-funded tools that collapse once projects end. 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 function only in demonstration settings. What determines whether AI creates lasting public value is whether the systems beneath it can be financed, maintained, governed, and improved over time. Sustained investment is what transforms technological solutions into public value.

Structures for Responsible Local Governance

Countries cannot govern what they do not control. Sovereignty, trust, and long-term value depend on local public governance institutions and structures determining architecture identifiers, platforms, rules, standards, hosting decisions, and procurement terms that underpin digital and AI systems. Local public governance 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 where AI relies on sensitive or population-scale data, or where core infrastructure, data pipelines, or system design are shaped by external vendors and partners. AI must not deepen dependency. Government ownership and public governance help ensure that AI aligns with national priorities rather than donor or vendor interests; that data access, consent, and secondary use are subject to public oversight; that countries avoid vendor lock-in and retain leverage over system evolution; and that accountability mechanisms and ethical guardrails reflect public values and legal obligations. Public health intelligence must remain a public good, planned, steered, and safeguarded by the state.

As countries expand digitized health records, **distinctions between electronic health records managed by providers (including government providers) to support system functions, and personal health records**, 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. Transparent consent frameworks, independent oversight, and participatory mechanisms are essential to create 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. Public governance is therefore not a procedural concern at the margins of AI adoption. It is central to whether AI functions as a matter of public strategy or remains a collection of loosely governed external actions with unclear or competing interests.

Public health intelligence must remain a public good: shaped, steered, and safeguarded by public institutions in the public interest. This is differentiated from the principle of formal state ownership alone. As AI systems become more capable and more deeply embedded in public systems, governments and the public will need institutions able not only to authorize them, but also to question them, adapt them, and hold them accountable over time.

Systems for Scalable and Equitable Impact

AI adoption in the health sector must be advanced with public health data systems that are inclusive, comprehensive, and connected. These systems should be understood as national public goods rather than stand-alone tools or temporary projects. Investments in foundational public health data systems and digital public infrastructure should therefore be prioritized.

For AI to improve, and not exacerbate inequities in public health outcomes, countries need data systems that reflect everyone, not only those who are easiest to count, visible to formal institutions, or 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 and digital systems 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 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 data systems.

When foundational data systems are inclusive, 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. Inclusion is not an added ethical consideration after systems are built. It is part of what makes public health intelligence accurate, legitimate, and effective.

Inclusive and interoperable datasets are not enough. AI-ready systems must also be able to act. **Public health intelligence generates value only when it is linked to defined decisions and actions, response pathways, public engagement and institutional coordination.** That requires stronger connections not only across health programs and levels of care, but also across the wider state systems that shape health outcomes, including identity, social protection, education, civil registration, and local administration. AI readiness depends on systems that reflect the whole population, connect intelligence across sectors and levels of government, and translate insight into timely and equitable public action.

Intelligent public health data systems begin with a digitized infrastructure for public health data. But durable foundations extend beyond data alone. They also include the institutional and technical conditions that allow public systems to absorb and sustain intelligence: interoperable digital architecture, stable connectivity, hosting and computing environments, maintenance capacity, and a workforce able to use and improve these systems in routine practice.

Building such foundations requires strong national foundations: long-term domestic financing that supports hosting, maintenance, updates, integration, and workforce capacity, not only initial build costs. It requires integrated national budgets and costed plans that prevent systems from becoming stranded after pilot phases. It also requires investment in enabling infrastructure, including reliable power, data storage and hosting environments, cloud governance rules, and country-owned or country-governed computing resources. Ministries and public institutions need the technical capacity not only to implement systems, but also to evaluate, monitor, and improve them over time rather than relying indefinitely on external actors. When these foundations are treated as shared national public infrastructure, later innovations can build on them rather than repeatedly starting from scratch. That lowers transaction costs, reduces duplication, and makes future innovation easier to absorb, govern, and scale. Strong foundations are not a competing priority to innovation. **They incentivize innovation, supporting long-term financial and social returns on investments.**

Conclusion

"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."
- Digital Health Implementation Expert

Artificial intelligence will not fix fragile public health systems. But it can make them more intelligent, responsive, and effective when the right foundations are in place. The value of AI for 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.

Across the Global South, AI is not arriving on a blank canvas. It is arriving in public health systems with their own histories, strengths, and unfinished business—systems that have been digitizing, registering populations, building surveillance networks, and stewarding data long before the current wave of attention to AI.

The evidence assembled in this report converges on a consistent finding. AI applications are proliferating faster than the institutional, digital, and governance foundations needed to sustain them. At the same time, this trajectory is not inevitable. Rwanda is treating foundational data systems as public goods. India is building digital public infrastructure that anchors AI in consented, longitudinal records. Rio de Janeiro is integrating data across sectors to anticipate outbreaks and climate-driven crises. Recife is using AI to surface signals of harm that previously went unnoticed in routine care. These are not finished examples. They are demonstrations that the alternative is real and within reach.

Three implications follow for how governments, funders, and partners should act now. **First**, foundations are not a competing priority to innovation—they are what make innovation impactful, governable, and equitable. The most useful investments in AI for public health over the next decade may not look like AI investments at all; they will look like investments in interoperable data architecture, civil registration and vital statistics, primary-care digitization, workforce capability, legal and ethical infrastructure, and long-term domestic financing.

Second, public governance is the precondition for public value. AI in public health cannot be left to vendors, donors, or external partners by default. Public institutions need the authority, the technical capability, and the institutional culture to set priorities, define conditions for deployment, monitor performance, and remain accountable.

Third, learning across the Global South is itself a strategic asset. No region in this report holds all the answers, but every region holds part of them. South-South exchange can shorten the path between ambition and durable capability.

None of this is to diminish the excitement about what the future of public health can look like with AI. It is to ensure that that future becomes a reality.

When foundational data systems are treated as national public goods—digitalized, publicly governed, inclusive, and sustainably financed—they do more than support today's programs. They also determine who will be visible to tomorrow's models, whose experience will shape predictions, and who will benefit from the decisions that follow.

Getting the foundations right will determine whether AI deepens fragmentation and inequities or helps build next generation public health systems that enables everyone, everywhere, to live their healthiest lives.


WINNIE

Appendices

Appendix 1: 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	Types of affiliations	Regions represented	Roles/titles	Number of respondents
Government	Ministries of Health	Nigeria, Kenya, Cameroon, Paraguay, Jordan, India, Brazil, India	Technical Advisors; Director of Strategic Information; Director of Policy and Research; Health Commissioner	11
Intergovernmental Organizations	World Health Organization and World Bank	Global, Latin America, Sub-Saharan Africa SEARO	Executive Director, Health Emergencies Program; Director, Digital Health and Innovation; Senior Health Specialist;	4
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 & Urban Epidemiologist; President & CEO; Fellow, Global Development; Director	12

*Updated for version 2.0

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 sub-themes, 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	Sub-Theme	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 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 problem definition 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.
	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.
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.
	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.
Promising Use Cases	**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.

Theme	Sub-Theme	Cross-Conversations Rapid Synthesis
	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 multi-sectoral data fusion can drive more targeted, equitable planning across government.

Table 1b: Insights and Recommendations

Theme	Sub-Theme	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, gender/SRH implementers, and data experts: Women, girls, 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.
	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.
Concerns & Risks	**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.
	Data Privacy, Security & Sovereignty Risks	Repeated concerns across ministries of health, WHO, Data.org, Brazil, Nigeria: data leaks, commercial misuse, non-consensual 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/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.
	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.

Theme	Sub-Theme	Cross-Conversations Rapid Synthesis
	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.
	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 and Legal Considerations

Theme	Sub-Theme	Cross-Conversations Rapid Synthesis
Governance & Legal	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.
	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.

Appendix 2: Foundational AI Readiness by Country

This table offers a high-level, directional snapshot of how countries Scan spanning Africa, South and Southeast Asia, Latin America, and the Middle East 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 when 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 uses GDHM's five-phase maturity scale, from Phase 1 to Phase 5, with higher scores reflecting more mature, nationally coordinated systems that support routine and standardized data exchange across digital health platforms. GDHM places this measure within its **Standards and Interoperability** domain.
- **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 pre-service and in-service training, formal training programs that produce a digital health workforce, and the maturity of public-sector digital health careers.

	Policy			Connectivity		Health Data	Work Force	
Country	National AI Policy/ Strategy Adopted or Approved (Yes/No)	Specifies Health (Yes/No)	Policy Type	IDI Score 2025	Intero-perability Phase (1-5)	WHO SCORE - Availability of latest data to monitor the health-related SDGs	Health work force (No Physicians Per 1000 People)	Digital Health work force Phase (1-5)
AFRICA								
Algeria	Yes	Indirect Mention	AI Strategy	86.1	-	56%	1	-
Angola	Draft	-	-	52.8	-	68%	0.2	-
Botswana	Draft	-	-	82.1	4	50%	0.4	2
Burkina Faso	Draft	-	-	-	2	62%	0.1	3
Benin	Yes	Yes	AI Strategy	47.4	4	58%	0.2	2
Burundi	Yes	Yes	AI Strategy	25.3	2	66%	0.1	3
Cabo Verde (Cape Verde)	Draft	-	-	80.6	2	73%	0.8	2
Cameroon	Yes	Yes	AI Strategy	46.3	2	70%	0.1	2
Central African Republic	No	-	-	-	2	28%	0	1
Chad	Draft	-	-	-	2	62%	0.1	2
Comoros	No	-	-	52.2	1	30%	0.4	1
DRC Congo	Draft	-	-	38	2	73%	0.2	2
Republic of the Congo	No	-	-	49.6	-	49%	0.2	-
Djibouti	Draft	-	-	64.4	-	37%	0.2	-
Egypt	Yes	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	Yes	AI Strategy	44	3	96%	0.1	5
Gabon	Draft	-	-	76.1	1	33%	0.5	1
Gambia	No	-	-	-	-	57%	0.1	-
Ghana	Yes	Yes	AI Strategy	70.6	1	66%	0.1	3
Guinea	Draft	-	-	-	4	46%	0	4
Guinea-Bissau	No	-	-	39	1	53%	0.2	1
Ivory Coast	Yes	Yes	AI Strategy	69.5	1	57%	0.2	2
Kenya	Yes	Yes	AI Strategy	56	5	83%	0.1	2
Lesotho	Yes	Yes	AI Policy	58.4	3	57%	0.2	2
Liberia	Draft	-	-	43.6	3	53%	0.2	3
Libya	Yes	Yes	AI Policy	87.8	-	69%	2.2	-
Madagascar	No	-	-	32.8	3	55%	0.2	2

Country	Policy			Connectivity		Health Data	Work Force	
	National AI Policy/ Strategy Adopted or Approved (Yes/No)	Specifies Health (Yes/No)	Policy Type	IDI Score 2025	Intero-perability Phase (1-5)	WHO SCORE - Availability of latest data to monitor the health-related SDGs	Health work force (No Physicians Per 1000 People)	Digital Health work force Phase (1-5)
Malawi	Draft	-	-	35.4	5	64%	0	4
Mali	Draft	-	-	42.9	2	57%	0.2	3
Mauritania	Yes	Yes	AI Strategy	58	1	53%	0.2	1
Mauritius	Yes	Yes	AI Strategy	86.3	-	72%	1.2	-
Morocco	Yes	Yes	AI Strategy	88.2	1	96%	0.7	1
Mozambique	Draft	-	-	32.4	3	72%	0.1	2
Namibia	Yes	Yes	AI Strategy	73.2	2	52%	0.5	2
Niger	No	-	-	-	3	60%	0	1
Nigeria	Yes	Yes	AI Strategy	52.9	3	51%	0.4	2
Rwanda	Yes	Yes	AI Strategy/ Policy	51.9	3	70%	0.1	3
São Tomé and Príncipe	Draft	-	-	57.1	2	66%	0.5	1
Senegal	Yes	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	Draft	-	-	85	3	69%	0.8	2
South Sudan	No	-	-	-	-	34%	0	-
Sudan	No	-	-	-	-	89%	0.3	-
Tanzania	Draft	-	-	53.2	5	60%	0.1	2
Togo	No	-	-	47.2	1	54%	0.1	1
Tunisia	Yes	Yes	AI Strategy	79.6	-	78%	1.3	-
Uganda	No	-	-	42.4	3	88%	0.2	3
Zambia	Yes	Yes	AI Strategy	60.3	3	83%	0.3	2
Zimbabwe	Yes	Yes	AI Strategy	56.8	2	89%	0.2	3
SOUTH AMERICA								
Brazil	Yes	Yes	AI Strategy	84.4	5	-	2.1	4
Paraguay	Draft	-	-	76.3	-	91%	3.9	-
Argentina	Draft	-	AI Plan	83.7	2	85%	5.1	4
Chile	Yes	Yes	AI Policy	93.4	3	94%	3.3	3
Colombia	Yes	Yes	AI Policy	77.2	2	87%	2.5	3
Peru	Yes	Yes	AI Strategy	77.6	-	92%	1.7	-
Venezuela	No	-	-	58.6	-	87%	1.7	-

Country	Policy: National AI Policy/ Strategy Adopted or Approved (Yes/No)	Policy: Specifies Health (Yes/No)	Policy: Policy Type	Connectivity: IDI Score 2025	Intero-perability Phase (1-5)	Health Data: WHO SCORE - Availability of latest data to monitor the health-related SDGs	Work Force: Health work force (No Physicians Per 1000 People)	Work Force: Digital Health work force Phase (1-5)
Bolivia	No	-	-	-	-	62%	1.3	-
Ecuador	Yes	Yes	AI Strategy	71.6	-	85%	2.3	-
Guyana	No	-	-	-	-	81%	1.4	-
Suriname	No	-	-	83.8	-	81%	1.4	-
Uruguay	Yes	Yes	AI Strategy	90	-	96%	4.7	-
SOUTH/SOUTHEAST ASIA								
India	Yes	Yes	AI Strategy for Health	-	4	89%	0.7	-
Cambodia	Draft	-	-	77.4	2	87%	0.2	1
Indonesia	Yes	Yes	AI Strategy	84.7	3	68%	0.7	3
Sri Lanka	Yes	Yes	AI Strategy	71.4	3	94%	1.2	3
Bangladesh	Draft	-	-	64.9	2	91%	0.7	3
Thailand	Yes	Yes	AI Strategy	91.9	3	83%	0.9	4
Nepal	Yes	Yes	AI Strategy	-	2	75%	1	3
Maldives	Draft	-	-	81.7	1	61%	2.2	2
Bhutan	Yes	Yes	AI Strategy	85.7	3	91%	0.6	2
Afghanistan	No	-	-	36.5	2	79%	0.3	1
Pakistan	Yes	Yes	AI Policy	56.4	2	83%	1.2	2
Vietnam	Yes	Yes	AI Strategy	86	3	77%	1.1	3
Philippines	Yes	Yes	AI Strategy	78	4	79%	0.8	3
MIDDLE EAST								
Saudi Arabia	Yes	Yes	AI Strategy	99.2	5	86%	3.4	5
Iran	Yes	Yes	AI Policy	87.9	-	98%	1.8	-
Iraq	Yes	Yes	AI Strategy	78.4	1	87%	1	1
Jordan	Yes	Yes	AI Strategy	84.7	2	81%	2.5	3

Appendix 3: Rapid Use-Case Landscape Scan Across the Global South

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 Global South region** (Africa, South and Southeast Asia, Latin America, and the Middle East) 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. 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. This process yielded 360 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, 264 examples remained. A qualitative synthesis of these examples identified five recurring functional groupings. 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.

Use Case Grouping	Description	Examples
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**, 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.
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.

Use Case Grouping	Description	Examples
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.
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 & front-line decision support:** Empower CHWs' national AI platform, HEP Assist call-center assistant, PATH's AI knowledge assistant to provide 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.
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.

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, systemwide 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

1 AI-Enhanced Diagnostics and Screening at Scale

Minimum

Human and institutional capacity:	Foundational public health data systems:	Digital public infrastructure and national digital ecosystems:	Legal, regulatory, and trust architecture:
Clearly defined clinical role for AI as decision support, not autonomous diagnosis.	Digitized imaging data; standardized imaging acquisition protocols and metadata; labeled datasets reflecting local disease patterns.	Basic IT infrastructure for image storage, transfer, and retrieval.	Data protection measures for clinical images.

Accelerators

Foundational public health data systems:	Human and institutional capacity:	Governance and public institutional ownership:
Locally representative training and validation datasets; interoperability between imaging 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.

Scale-critical

Governance and public institutional ownership:	Legal, regulatory, and trust architecture:	Financing and institutionalization:	Human and institutional capacity:
Government ownership or control over deployment architecture and data pipelines; integration into national referral, quality assurance, and surveillance systems.	National regulatory pathways, liability clarity, post-deployment monitoring, audit, and recalibration mechanisms.	Long-term financing for compute, maintenance, upgrades, and support.	Scaled institutional capacity to assess bias, safety, and real-world effectiveness.

2 AI for Surveillance, Pattern Recognition, and Early Warning

Minimum

Human and institutional capacity:

Ability to interpret alerts, validate outputs, and connect findings to response.

Foundational public health data systems:

Sustained routine data flows from surveillance systems; basic integration of core epidemiological data sources.

Governance and public institutional ownership:

Clearly defined public health decisions or responses linked to alerts.

Accelerators

Foundational public health data systems:

Integration of multi-source data to detect patterns and anomalies earlier than traditional surveillance; continuous validation of predictions against observed outcomes.

Digital public infrastructure and national digital ecosystems:

Stronger interoperable infrastructure to support multi-source exchange and longitudinal analysis.

Scale-critical

Governance and public institutional ownership:

Government-owned, interoperable data architecture supporting longitudinal analysis.

Legal, regulatory, and trust architecture:

Governance and ethical oversight to manage data quality, bias, privacy, and equity risks.

Financing and institutionalization:

Long-term financing for hosting, maintenance, and model monitoring.

Cross-sector coordination and public action:

Institutional pathways for alerts to trigger coordinated response.

3 AI for Public Communication and Behavior Change

Minimum

Human and institutional capacity:

Capacity to define target behavior and population and oversee content use in practice.

Digital public infrastructure and national digital ecosystems:

Trusted digital channels.

Legal, regulatory, and trust architecture:

Basic consent, privacy, and safeguarding measures.

Accelerators

Human and institutional capacity:

Localization of language, tone, and cultural context.

Foundational public health data systems:

User segmentation and adaptive personalization based on reliable data inputs.

Cross-sector coordination and public action:

Integration with human support or referral pathways.

Scale-critical

Governance and public institutional ownership:

Public governance over content standards and safeguards.

Legal, regulatory, and trust architecture:

Regulatory clarity on boundaries of automated health advice.

Financing and institutionalization:

Sustainable financing for moderation, updates, and user support.

Human and institutional capacity:

Ongoing institutional capacity to monitor harm, trust, and effectiveness.

4 AI for Frontline Worker Support and Service Delivery

Minimum

Human and institutional capacity:

Clear role definition; defined escalation pathways for uncertainty or low-confidence outputs.

Digital public infrastructure and national digital ecosystems:

Device access and minimum connectivity.

Accelerators

Human and institutional capacity:

Localization for language, clinical context, and practice norms; continuous user feedback and iterative improvement.

Governance and public institutional ownership:

Integration with supervision, referral, and reporting systems.

Scale-critical

Governance and public institutional ownership:

Standardized accountability and decision protocols.

Human and institutional capacity:

Long-term workforce enablement and digital literacy strategies.

Legal, regulatory, and trust architecture:

Ongoing monitoring for bias, safety, and unintended harm.

Financing and institutionalization:

Long-term support for adoption, maintenance, and improvement.

5 System Intelligence, Planning, and Resource Allocation

Minimum

Human and institutional capacity:

Capacity to interpret outputs and connect insights into policy and planning decisions.

Governance and public institutional ownership:

Clearly defined policy decisions, the intelligence will inform.

Legal, regulatory, and trust architecture:

Legal or policy basis for cross-sector data use.

Foundational public health data systems:

Minimum viable data linkage approach.

Accelerators

Governance and public institutional ownership:

Governance mechanisms for data linkage quality and bias management.

Cross-sector coordination and public action:

Multi-agency coordination and shared operating procedures.

Human and institutional capacity:

Explainability of analytic outputs for planning and accountability.

Scale-critical

Governance and public institutional ownership:

Durable data-sharing agreements and oversight bodies.

Legal, regulatory, and trust architecture:

Safeguards against misuse, surveillance, or exclusion.

Human and institutional capacity:

Institutional capacity to translate insights into funded action.

Financing and institutionalization:

Long-term institutional support for planning, budgeting, and system use.

5a Data Quality Automation and Population-Level Analytics

Minimum

Human and institutional capacity:

Capacity to define analytic objectives and review automated outputs.

Foundational public health data systems:

Government-defined data standards and coding systems; access to administrative, surveillance, or registry datasets; clear analytic objectives and auditability of outputs.

Accelerators

Foundational public health data systems:

Harmonized metadata and master facility/workforce lists; feedback loops to data producers to improve upstream quality.

Governance and public institutional ownership:

Stewardship roles for reviewing and validating automated outputs.

Scale-critical

Governance and public institutional ownership:

Public ownership of data pipelines and analytic logic.

Legal, regulatory, and trust architecture:

Oversight and accountability for automated classification and harmonization.

Digital public infrastructure and national digital ecosystems:

National interoperability frameworks and shared identifiers.

Financing and institutionalization:

Stable financing and institutionalization within routine planning and reporting.

5b Administrative and Workflow Optimization

Minimum

Human and institutional capacity:

Frontline user acceptance and basic digital access.

Governance and public institutional ownership:

Identification of high-volume, rule-based administrative processes; baseline workflow mapping and performance metrics.

Accelerators

Governance and public institutional ownership:

Integration with existing government systems and platforms; workflow redesign alongside automation, not automation alone.

Human and institutional capacity:

Training and change management for staff.

Scale-critical

Governance and public institutional ownership:

Governance mechanisms to ensure efficiency gains translate into service improvement.

Legal, regulatory, and trust architecture:

Safeguards against vendor lock-in and opaque automation.

Financing and institutionalization:

Long-term budget lines for system maintenance and support.

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Updated on May 12, 2025