Closing the Evidence Gap: How to Improve the Monitoring of AI Impacts in Africa

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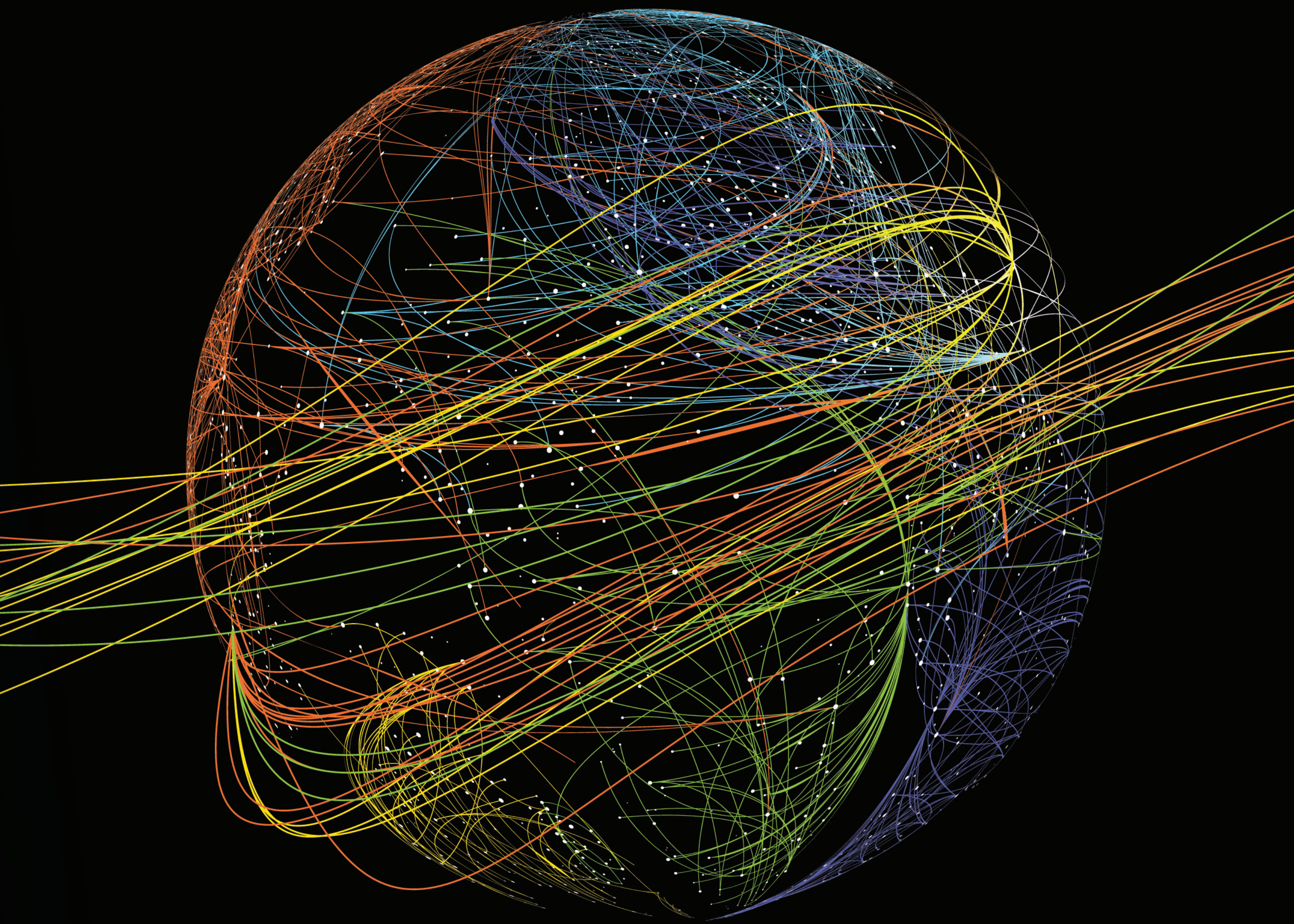

ILINA PROGRAM

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ABOUT THE ILINA PROGRAM

ILINA is an African-led organisation dedicated to advancing AI safety through research, policy engagement and talent development.

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Executive Summary

AI adoption is accelerating across the African continent, with predictions of significant benefits and equally significant harms. AI is increasingly being adopted by governments and private sector institutions in critical sectors such as agriculture, health, education and finance, and the uptake of general-purpose AI is also growing among individual users.

In response, African policymakers are developing governance frameworks that aim to harness the benefits of AI while simultaneously mitigating the risks, but they are currently 'regulating under uncertainty'. At least 15 African countries had a national AI strategy or policy by the end of 2025, and the African Union released a Continental AI Strategy in 2024. However, these policymakers lack the evidence to verify the predicted impacts of AI in Africa, which range from transformative economic growth to severe societal harms. The systems needed to collect such evidence remain underdeveloped — there are minimal government-led efforts to monitor AI impacts and no dedicated AI incident databases on the continent. The research on AI impacts also remains cursory.

This report seeks to address this evidence gap. It offers recommendations on how to improve the monitoring of AI impacts in Africa, and in doing so, aligns with African governments' stated desire to increase research and evidence on AI impacts on the continent. The report recommends monitoring of two high-level categories of impacts: impacts that are easily observable and impacts that are not easily observable. Monitoring of the first category involves direct data collection whereas monitoring of the second category involves further research and analysis. Monitoring of these impacts should extend to AI adoption by governments and private sector institutions in critical sectors as well as individual adoption of AI.

This AI impacts data can serve several critical purposes. It can enable evidence-based AI policymaking and ensure that African governments' AI policies reflect local realities rather than the priorities and assumptions of the Global North, which currently dominate in AI policy research. It would also support international information-sharing arrangements that can position African countries as credible partners in global AI governance, and guide other decisions related to investment, model improvements and accountability efforts by developers, regulators and civil society.

Africa's experience in strengthening health data collection offers a practical model, though not a perfect analogue, for building AI impact monitoring systems. African countries have improved their health information systems through government and donor investment, decentralisation of data collection to community levels, adoption of digital tools including mobile-enabled technology and participatory surveillance, and investment in health journalism. These advances demonstrate that robust data collection is achievable even in resource-constrained settings when grounded in local ownership, multi-stakeholder collaboration and appropriate technology.

This report recommends four mutually reinforcing strategies to close the evidence gap. These strategies are directed at African policymakers, as well as researchers, journalists and donors, and account for the diverse capacities and contexts across the continent.

First, African governments should lead efforts to monitor AI impacts, both through their own monitoring and by mandating reporting from other actors. Existing apparatus, like national statistical offices and ministries, can be leveraged to integrate AI impact indicators into their data collection efforts. Ministries are well-placed to monitor impacts in the sectors they oversee, while national statistics offices and ICT ministries can track the cross-cutting effects of general-purpose AI and establish national AI incident databases. Because African countries vary greatly in statistical capacity, these efforts must be calibrated accordingly. Countries with stronger statistical systems can draw on them more extensively to collect more varied AI impacts data across many sectors and individual use. They might also be better equipped to monitor AI impacts that are not easily observable, through research and empirical analysis, and to invest in dedicated mechanisms such as AI incident databases. Countries with weaker statistical capacity can begin from their existing strengths, such as by adding an AI component to the specific surveys they conduct consistently, and expand monitoring as statistical capacity grows. Across both categories, collaboration with non-state actors can help bolster monitoring of AI impacts.

African governments can also mandate post-deployment monitoring and incident reporting from companies whose AI models are deployed in their jurisdictions. Additionally, African governments can seek disclosures that direct them on where to monitor for AI impacts. This can be done through pursuing data-sharing partnerships with AI developers to obtain country-level usage data and requiring disclosure of AI use and intended use in in high-stakes domains.

Second, monitoring should be decentralised to complement government-led monitoring. Beyond government efforts, independent researchers, civil society organisations and other non-governmental organisations (NGOs) can conduct research, including field research, to trace AI impacts, establish independent incident tracking databases, and develop other tools to support the reporting of AI harms. This decentralisation serves two purposes. It can fill in gaps left by government efforts and it can enable independent scrutiny of government AI use.

Third, there should be investment in technology journalism. Technology journalists can play a critical role in identifying and documenting the societal effects of AI systems, raising public awareness and prompting policy responses. However, technology journalists in Africa face challenges similar to those that have historically limited health journalism, including inadequate funding, limited technical knowledge and insufficient editorial interest. Donors can address these gaps by supporting three categories of technology journalists: investigative journalists, digital media journalists, and community-based journalists. Donors can support these technology journalists by investing in journalism fellowships and channelling this funding through trusted media centres and organizations.

Finally, digital participatory monitoring represents a particularly promising and scalable approach for the African context. Drawing on proven models from health surveillance, both state and non-state actors monitoring AI impacts can deploy open submission platforms, mobile-based reporting tools and social media surveys to enable individuals and organisations to report AI-related harms and experiences. Existing African tools such as Ushahidi, which has facilitated citizen-driven reporting on issues ranging from human rights violations to climate action, demonstrate the feasibility of this approach at scale. Successful implementation will require attention to the continent's uneven internet connectivity and leveraging the expanding access to mobile phones. It will also require investment in public education about AI, and the use of local languages and familiar platforms in order to boost public engagement. Finally, digital participatory monitoring must seriously account for privacy and data protection considerations, particularly when reports involve sensitive information from individuals, organisations or public institutions.

Realising these recommendations will require coordinated action from African governments, researchers, journalists, civil society and donors. African governments will need to invest more in statistical capacity, especially in the data analysis and expertise required to establish the relationship between AI adoption and observed impacts. Donor funding can support both government and non-state efforts, but should draw on lessons from health data collection by prioritising locally owned initiatives, avoiding the creation of parallel systems and enabling collaboration between state and non-state actors where appropriate.

Ultimately, building Africa's capacity to monitor AI impacts is not only a prerequisite for sound domestic AI policy but also the foundation for the continent's credible participation in global AI governance.

1 Introduction

> **We are in the midst of a technological revolution that will fundamentally alter the way we live, work, and relate to one another. Artificial intelligence (AI) promises to transform many aspects of our society and economy.[1]**

AI adoption[i] is increasing across the world, and Africa is no exception.[2] Governments and private sector institutions across Africa are adopting AI,[ii] and pushing for increased adoption of AI,[3] to solve the continent's pressing problems in agriculture, healthcare, education, finance, public service delivery, security and other critical sectors.[4] The adoption of generative AI tools like ChatGPT and Claude by individual users is also growing.[5] As AI adoption grows, there are increasing predictions of what the impacts of AI will be. These range from apocalyptic to utopian.[6] In Africa, predictions range from claims that AI will positively transform the continent,[7] to claims that AI will pose severe risks that may result in catastrophic harms for African people and systems.[8]

On the optimistic end, some estimates, for example, paint the potential benefits of AI to the African economy as ranging from $2.9 billion to $4.8 billion by 2030.[9] African countries also expect that AI will revolutionise critical sectors of their economies. In agriculture, for example, AI is expected to increase efficiency and effectiveness resulting in increased yields and reduction in poverty.[10] In education, there is hope that AI will make education systems more accessible, efficient and personalised while in healthcare, better-tailored, higher quality and accessible health is expected.[11] Similar benefits are expected in financial services, energy and transportation, and in public service delivery.[12] As a result, investment in AI innovations and infrastructure is increasing on the continent.[13] The Gates Foundation and OpenAI, for example, have recently announced their plan to invest $50million to accelerate adoption of AI tools in health clinics and communities in a number of African countries.[14]

On the other hand, there have also been predictions of significant harms to African countries and African peoples, that could stem from misuse, accidents and even loss of control over AI.[15] These include harms like bias, discrimination and labour displacement as well as more catastrophic harms such as increased armed conflict, more repressive and enduring authoritarianism and unparalleled manipulation, among others.[16] Some harms are already materialising. For example, AI is supercharging electoral disinformation on the continent, as evidenced by the 2023 Nigerian presidential election and the 2024 South African elections,[17] though the impact of such disinformation on electoral outcomes remains contested.[18]

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i AI adoption refers to the integration and use of AI by individuals and organisations in their activities.

ii Throughout this report, AI broadly refers to the machine-based systems that are able to 'show human-like intelligent behaviour characterised by certain core competencies, including perception, understanding, action, and learning'. It includes both narrow AI, which is designed for particular domains, and general-purpose AI, such as generative AI models. *See* Bernd W. Wirtz et al, An ecosystem framework of AI governance, in Justin B. Bullock et al (eds) The Oxford Handbook of AI Governance, Oxford University Press, 2024, 401.

In recognition of these potential impacts of AI, African policymakers have begun developing frameworks to govern AI at the national and continental levels. At least 15 African countries had a national AI strategy or policy by the end of 2025, and the African Union released a Continental AI Strategy in 2024.[19] However, African policymakers are currently operating in a regulatory environment characterised by incomplete information and lack of consensus on the relative benefits and risks of AI. They are 'regulating under uncertainty'.[20] As AI policy and regulation continue to take shape on the continent, it is imperative that the degree of uncertainty is lowered by ensuring that African policymakers and regulators have more evidence to rely on.

One kind of evidence that will make a significant difference for African AI policymakers is robust data on the impacts that AI is already having in Africa (AI impacts data). AI impacts data will be especially welcome since African governments have already signalled their interest in strengthening the research and evidence on AI impacts in African countries.[21] Such data can ensure that African AI policy is based on locally relevant evidence and responds to the unique needs of local communities. It could also serve as the basis for collaboration with other governmental and intergovernmental bodies such as the European Union (EU)'s AI Office, as suggested by other studies.[22]

However, monitoring of AI impacts in African countries is currently limited. There is minimal government-led monitoring despite commitments to do so.[23] And while several research organisations and non-governmental organisations are researching and documenting some AI impacts,[24] this work on AI impacts remains quite cursory[25] and ancillary to the focus of their work. The primary focus has been tracking AI adoption and highlighting use cases in Africa, with limited discussion on the impacts of these use cases.[26] There are no dedicated AI incident databases on the continent either.[27] There is, therefore, a need to systematise monitoring and documentation of AI impacts, making it more extensive and consistent.

This report is an initial response to this evidence gap. It offers concrete recommendations on how to improve monitoring of AI impacts in Africa, considering the contextual realities of African countries. Ultimately, the report makes recommendations relating to government-led monitoring, decentralised monitoring by non-state actors, technology journalism to report on AI harms and investing in digital participatory monitoring. These recommendations are directed at African policymakers, researchers, journalists and donors.

The report begins by defining the data that needs to be collected and explaining why this data is important in section 2. In section 3, it dives into health data collection as a case study of a critical policy area where African countries have improved their monitoring and details the strategies that have proven successful. Following this, the report makes recommendations as explained above.

2 The scope and rationale for monitoring AI impacts in Africa

2.1 The scope of monitoring of AI impacts needed in Africa

Monitoring of AI impacts in Africa needs to be extensive enough to cover the impacts arising from both adoption by governments and private sector institutions in critical sectors, and individual adoption. Furthermore, monitoring of AI impacts needs to extend to positive impacts, as this can inform efforts to harness AI benefits as well as negative impacts, as this can inform efforts to mitigate AI harms.[iii]

Given the increasing adoption of AI across many different sectors and uses, AI impacts in African countries are likely to be diverse and widespread.[28] The remainder of this subsection offers a high-level classification of these impacts to guide how monitoring should be structured, before turning to more granular details that should be collected.

2.1.1 A high-level classification of impacts to be monitored

Some AI impacts are likely to be directly observable while others are not. The Centre for Security and Emerging Technology (CSET) classifies harms on this basis, noting that one of the main differences between tangible and intangible harms is how observable, verifiable and definitive they are. Tangible harms, such as harms to physical health and safety, financial loss, and damage to property, infrastructure and the environment, are more discernible because a third party can observe them as they occur and ascertain that harm occurred.[29] On the other hand, intangible harms, such as the creation and spread of detrimental content (such as misinformation and hate speech), bias and differential treatment, violation of human rights, harm to democratic norms and infringement of privacy, reputational harm and psychological harm, are harder to observe. This is because though we can observe the event causing harms, the harms do not have a physical effect and are thus not expressed in observable ways, and people may dispute whether these harms actually occurred.[30]

However, even within these two broad categories, observability exists on a spectrum rather than as a binary distinction. For example, deepfake pornography[iv] may be observed and documented more easily than its secondary impacts like reputational harm and psychological harm. Similarly, an increase in disinformation may be more discernible than the secondary impacts that result from it, such as the impacts of disinformation on electoral outcomes and on trust in societal institutions.

[iii] Currently, most work is on the monitoring and reporting of AI harms and incidents. This report proposes that the monitoring of AI benefits is also critical for African countries.

[iv] Some research, such as the CSET taxonomy, might classify this as an event leading to harm, whereas the author of this report argues that an increase in non-consensual deepfake pornography is itself a form of harm.

Additionally, the observability of an impact could depend on its scale, frequency and temporality. Some might crystallise in a single, dateable event, such as a mass or individual layoff at an organisation. Others crystallise as systemic impacts, and as trends over a period of time. For example, industry-wide or nation-wide labour impacts can only be observed in aggregate. Monitoring of single events is more tractable, including through incident databases, whereas monitoring of systemic impacts might need more analysis and research to ascertain the impact. For example, monitoring of systemic labour impacts could entail collecting data on AI usage and linking this data with other existing data on economic indicators like employment, hiring and wages.[31] Monitoring AI's impact on agricultural productivity would similarly involve collecting and analysing data on AI usage in agriculture together with data on agricultural productivity over a period of time.

Therefore, monitoring of AI impacts may take the form of direct data collection of AI impacts or a more complex form involving further analysis and research.

2.1.2 The AI impacts data to be collected

Monitoring of AI impacts, whether directly observable or not, should extend beyond merely describing impacts to include other critical components. Research on AI incident reporting has already explored what data should be collected in relation to AI harms.[32] Though limited, some studies have also considered the details that should be collected for beneficial impacts.[33]

The details pertaining to harms include, first, the type of harm that has occurred. This refers to whether the harm is physical (resulting in physical injury and death); environmental (for example, soil contamination, water pollution and air pollution); economic and financial (such as financial loss or damages and harm to property); reputational (individual and organisational reputation); harm to the public interest (involving critical infrastructure); human rights and fundamental rights; or psychological (affects mental health). The second detail is the details of the affected parties. This could cover individuals and entities, and whether they were users or non-users of the models or systems. The third detail is the contributing factors, and whether these were technical such as malfunctions, system vulnerabilities, data poisoning and concept drift or non-technical, such as user misuse, weak governance or a lack of safeguards. Finally, this should cover data on the severity of harm, including how acutely the harm impacted the affected parties (level of severity or scale); whether it is possible to restore the affected parties to a situation at least equivalent to their situation before the impact (remediability); whether any of the affected parties was disproportionately affected by the harm (proportionality or distribution of harm); an estimate of how many affected parties there are (exposed population size); how long the harm was experienced by the affected parties (duration) and the rate at which the affected parties experience harm (frequency).[34] Monitoring beneficial impacts can similarly involve collecting many of these details including the severity or scale, duration and frequency, among others.[35]

Importantly, efforts to collect these details need to consider that these details could be spread between different parties.[36] For example, affected parties could have details on the type of harm and severity of the harm that they have experienced, but not the contributing factors or whether any other parties have been affected. Actors (state and non-state) monitoring AI impacts may thus need to expand their coverage to different parties, and also coordinate with other actors to share information that paints a more complete picture of the AI impacts.[37]

In Africa, monitoring should extend beyond recording the mere occurrence of impacts to capturing the surrounding circumstances in detail. Such granularity makes the data more actionable, as discussed in the next subsection.

2.2 Why AI Impacts Data Matters for Africa and Beyond

2.2.1 Informing evidence-based policymaking in Africa

As African governments continue to develop AI governance frameworks, AI impacts data would provide critical evidence for evidence-based policymaking.[38] Already, some of this data is informing the development of national AI policies and strategies across the continent.[39] For example, evidence of the benefits of AI-powered solutions in agriculture have bolstered the Kenyan government's motivation to support AI adoption in agriculture and other sectors.[40] However, national AI policies and strategies are also relying heavily on projections such as on the expected impacts of AI on labour market.[41]

AI impacts data can support policymaking in various ways. First, it can inform future policies and legislation, including by testing whether the projections underlying the current policies hold true in practice.[42] Data on AI harms, in particular, can also inform decisions on the efforts that should be taken to mitigate the observed harms or failures, the regulatory requirements or safeguards that should be put in place to prevent future harms and over time, whether existing safeguards are effective.[43] Importantly, AI impacts data can inform a variety of national policies such as labour policies, cybersecurity policies and education policies, and not just AI policies. This is especially the case for data on AI impacts in the specific high-impact sectors. Finally, this data can inform public resource allocation on a continent that has 'numerous resource constraints' and thus needs a 'strategic approach to maximise the impact of limited resources'.[44] The data can thus guide decisions such as which AI-powered solutions and AI use cases African governments should channel public funding into.

Importantly, the data on AI impacts within Africa can ensure that this evidence-based policymaking is informed by locally relevant evidence rather than being shaped by external actors, values and motivations. Knowledge on how AI risks might manifest in African contexts is still quite limited.[45] Most of the research and discourse on AI risks and safety is from the Global North, and thus reflects the Global North's priorities and assumptions and overlooks the unique realities of African contexts.[46] For example, discussions on fairness are often based on Western constructs like race and fail to account for other nuances of fairness such as tribal affiliation, religion and socioeconomic status that are critical in African contexts.[47] If based on this limited knowledge base only, African

AI policies may miss harms that manifest uniquely in the African settings. Data on AI impacts within Africa is thus essential to ground African governments' policies in local realities.[48]

2.2.2 Advancing African and global AI safety through information sharing

AI governance is a global governance challenge that requires international collaboration.[49] One key form of collaboration is information sharing, which 'remains a necessary ingredient for AI risk reduction, enhancing both resilience and preparedness'.[50] By sharing information on AI impacts that have manifested in their jurisdictions, and are likely to manifest in other jurisdictions with other governments and intergovernmental bodies like the EU AI Office and the International Network for Advanced AI Measurement, Evaluations and Science, African countries can enhance their own safety and global preparedness.[51]

For partnering governments or intergovernmental bodies, this information could trigger and inform regulatory responses. Some AI impacts data could, for example, prompt and/or enable the EU AI Office to enforce the General-Purpose AI (GPAI) Code of Practice[v] in various ways. First, information on incidents from GPAI models with systemic risks[vi] could prompt the EU AI Office to assess compliance with the Code of Practice. The EU AI Office could assess whether AI developers have fulfilled obligations like providing channels for communicating incidents and using this information in subsequent risk identification.[52] Second, AI incidents data could prompt the EU AI Office to evaluate GPAI models with systemic risks.[53] Information on incidents can be useful in identifying the underlying capabilities, vulnerabilities and potential risks of GPAI models,[54] and in noting trends of cross-border incidents.[55] This data from African countries could thus serve as an early warning mechanism that prompts the EU AI Office to evaluate models deployed in the EU for systemic risks.[56] Finally, based on this information, the EU AI Office could require AI developers to undertake certain safety-increasing actions, such as putting in place safety mitigation measures, restricting the making available of the model on the market or withdrawing or recalling the model.[57] AI impacts data from African countries could thus enhance the EU's preparedness and safety.

Importantly, sharing this data could also advance African safety. To begin with, the enforcement of frameworks like the EU Code of Practice is likely to have a global effect on safety that transcends the EU.[58] The Code is likely to promote safety as it formalises and strengthens AI safety practices along the entire cycle of risk management.[59] And since the safety measures mandated by the Code are implemented at the model level rather than the system level, and the cost of developing or customising different models for different jurisdictions is high, developers who wish to place their models on both the EU market and other markets are likely to treat the Code of Practice as the baseline standard for their safety measures everywhere.[60] As such, the EU Code of Practice is

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[v] The GPAI Code of Practice is a voluntary code designed to help developers of GPAI models comply with their obligations under the EU AI Act.

[vi] These are models that are trained on a cumulative amount of compute greater than 10^25 floating-point operations (FLOPS). They include many of today's frontier AI models such as GPT 4.5, Gemini 1.0 Ultra, Claude 3 Opus and Grok 4.

likely to promote safety not just in the EU, but in other jurisdictions where the covered models are deployed, including African countries.[61]

Moreover, this information can also be the basis for African countries to negotiate for reciprocal information sharing by the EU and other partners, thus garnering African countries information needed to advance their safety and security goals themselves.[62] African countries, for example, could also negotiate for information on incidents that occur in the EU as well as information on training data and how evaluations were conducted. Developers are required to share the information on training data and evaluations with the AI Office through their Safety and Security Frameworks and their Safety and Security Model Reports.[63] Such information can be used by African countries to assess (i) whether the training data was diverse, unbiased and representative which is a concern for many African countries, and (ii) whether there are gaps in the developers' evaluations as they pertain to African countries that need to be filled in with plural, multilingual and multicultural evaluations from African countries.[64]

Sharing AI impacts data, therefore, stands to be a key way for African countries to collaborate with other governmental and intergovernmental bodies, and in doing so, advance both their own safety and global safety.[65]

2.2.3 Guiding investment, model improvements and accountability

Finally, this data could be instrumental in guiding other stakeholders in decisions on investing in AI, development and improvement of AI models and systems, as well as seeking redress for AI harms.

For investors, AI impacts can serve a critical role in decisions about where to direct resources by offering evidence-based insights on where AI is having a real positive impact. It can, therefore, inform which AI solutions investors should fund and scale up, including in the high-impact sectors.[66]

For developers, AI impacts data can lead to model and system improvements and efforts to develop safer, more secure and trustworthy AI systems by improving the developers' knowledge of AI-related harms.[67]

Finally, AI impacts data fuel accountability, by prompting activists and other watchdog organisations to seek redress for harms, through legal action and seeking compensation for affected parties.

3 Evidence from improvements in health data collection

Much like AI impacts data, health data serves a critical role in decision-making. It is 'necessary to improve health outcomes, guide identification of health problems and population needs, inform planning and design of health interventions to address public health problems, guide decision making during allocation of scarce resources, and provide opportunity for monitoring and evaluating progress towards achievement of health goals'.[68] The need for health data in Africa has been especially highlighted by the emergence and re-emergence of large outbreaks of communicable diseases like meningitis, cholera, yellow fever and measles, which led to efforts to improve disease surveillance since the 1990s.[69] In 2008, African countries also committed to improving their broader health information systems (HIS) [vii] in order to improve their healthcare delivery.[70]

Continuous efforts to improve African health information systems have resulted in better health data collection in several African countries. The volume of health data has increased, with data collection capturing a wide variety of data types like disease-specific prevalence and incidence data, maternal and child health data, morbidity and mortality data, household data like sanitation, and demographics and registration data, among others.[71] Monitoring of health outcomes,[viii] in particular, has also improved as a result of these broader efforts to improve African HISs. Several African countries now collect more data on health outcomes like 'Maternal, Neonatal, and Child Health (MNCH) mortality and morbidity data that informs health service delivery and development of interventions'.[72] The sources and tools used to collect this data have also increased.[73]

However, despite the strengthening of health data collection in Africa, there are still gaps in health data accuracy, completeness and timeliness. While more data is collected, much of it is typically incomplete and the quality poor due to lack of standardisation and interoperability between the different sources of data and management systems.[74] Many African countries also still rely on paper-based systems which often cause delays and errors.[75] Finally, many African countries lack regulatory frameworks that guide the development and management of their HIS. This has resulted in poor coordination, such as with private sector and non-governmental organisations to share health data collected by these organisations.[76]

[vii] According to the World Health Organization, a health information system refers to 'a system that integrates data collection, processing, reporting and use of the information necessary for improving health service effectiveness and efficiency through better management at all levels of health services. See, World Health Organization (WHO), Developing health management information systems: a practical guide for developing countries, 2004, 3 - https://iris.who.int/server/api/core/bitstreams/3aa7ef4d-f258-4f55-bef5-96797684c583/content on 24 January 2026.

[viii] Health outcomes or status is only one of the indicators monitored by health information systems. Health outcomes, including mortality, morbidity, disability and well-being, generally depend on health determinants as well as health interventions. See, Health Metrics Network and World Health Organization, Health Metrics Framework, Framework and Standards for Country Health Information System Development: Second Edition, 2008, 20 - https://www.afro.who.int/sites/default/files/2017-06/AHO_Country_H_Infos_Systems_2nd_edition.pdf on 20 April 2026.

Notwithstanding these challenges, health information systems in Africa are among the more developed national data systems on the continent,[77] and given the improvements witnessed, health data collection provides a good case study on how to improve monitoring in a critical policy area. That said, health data collection is not a perfect analogue of monitoring of AI impacts. To begin with, health data collection entails collection of a variety of indicators, including health determinants, health inputs and outputs, health status and health outcomes.[78] Of these, health outcomes is the closest comparator to AI impacts. However, as the improvements in collection of data on health outcomes have mostly arisen from the broader efforts targeting health data collection, the available research is mostly on the factors that have strengthened health data collection broadly. Importantly, even though the other aspects of health data collection are not directly comparable to AI impacts, some of the factors that have improved these other aspects seem extremely promising for AI impacts monitoring. This reports thus highlights both the factors that have improved collection of data on health outcomes specifically, and those that have improved other aspects of health data collection.

In any case, there are also critical differences between health outcomes and AI impacts that matter. The main difference arises from the general nature of AI – which means that AI is being adopted across many sectors and AI impacts will manifest in these different sectors without a dedicated regulator or government ministry in charge of monitoring these impacts. In comparison, most health outcomes are monitored through health information systems and hence primarily fall under the purview of a specific ministry or regulator (the health ministry) in most African countries. Another critical difference is that it might be easier to attribute health outcomes to health issues, than it is to attribute AI impacts to AI. Attributing AI impacts to AI, as opposed to other factors, remains a technical challenge in part because of our inability to interpret the internal processes of AI systems and how they come to their decisions.[79]

However, these differences are not insurmountable. To begin with, health outcomes are also varied. While some are health-related such as mortality and morbidity, there are other socio-economic impacts such as on education and labour markets, among others.[80] Furthermore, quite like AI impacts data, a lot of data on health outcomes and other health-related data is actually generated outside the health sector. For example, data on births and mortality is gathered from population censuses, civil registration systems and household surveys, which are managed by the ministries of interior, census bureaus and national statistical offices.[81] Comprehensive collection of health data is enabled by coordination between many ministries and government actors,[82] in the way that monitoring of the impacts of AI is bound to be.

3.1 Factors that have contributed to the strengthening of health data collection in African countries

The strengthening of health data collection in African countries has been driven by a combination of factors, including government and donor investment, decentralisation of data collection to the community level, the adoption of digital tools, and investment in health journalism. Some of these factors relate directly to monitoring of health outcomes while others relate to improvements in health data collection broadly, which often includes data on health outcomes.

3.1.1 Government and donor investment in health data collection sources, tools and personnel

African governments have invested in improving their health information systems in various ways. Many African countries have rolled out the open-source DHIS2 software platform to support routine health data collection.[83] Additionally, some governments have invested in the infrastructure required to improve data collection, such as by training officers in health information management and providing computers to digitise health data collection and compilation.[84]

However, government investment has often been inadequate,[85] and external donor support has filled in the gaps by providing the infrastructure and personnel required to collect health data.[86] Donor funding has enabled collection of data on health outcomes through funding specific data sources like civil registration systems[87] and surveys. Until 2025, the United States Agency for International Development (USAID), for example, funded the Demographic and Health Survey (DHS) which has enabled more rigorous collection of data on maternal and child mortality rates and the causes of these deaths, in most African countries.[88] In some African countries, the DHS had been the only source of data on maternal mortality.[89]

Unfortunately, donor funding that focuses on data sources and specific diseases has often resulted in parallel systems of health data collection and fragmentation of African HISs.[90] The parallel donor-supported systems have often reflected donors' priorities and sometimes undermined national programmes.[91] To resolve these issues, some donors have offered support aimed at strengthening national HISs generally.[92] This sort of support has allowed African countries to define their own priorities and what methodology to take in improving their HISs. As such, some partnerships have resulted in more data collection tools like registers in some countries, the introduction of ICT innovations like electronic medical record (EMR) systems in others and improvement of community-level health data collection.[93]

This kind of support, which aims to strengthen national HISs, has been especially successful because it has made it possible to support local priorities instead of establishing parallel systems, which the other type of support had led to.[94] Furthermore, this support has allowed stakeholders, including at lower levels such as districts and the community, to participate in the design of the solutions to the problems in their health information systems.[95] These two factors have made these interventions sustainable,[96] and can guide donor funding of collection of AI impacts data. Donors, for example, may evaluate which interventions recommended in section 4 to support using this criterion. They can choose to fund interventions by local researchers, media and civil society that are developed together with local stakeholders or at least, that take into account local realities. This will avoid establishing parallel systems that are divorced from local efforts.

3.1.2 Decentralization of health data collection

Many African countries have strengthened their health data collection, including on health outcomes, by decentralising the collection to lower levels like the community level, and thus improving health data collection in remote and rural areas. This has been through investing in Community Health Information Systems (CHISs) and Community-Based Surveillance of diseases and health events (CBS).[97] CHISs and CBS, which involve community health workers collecting health data in their communities,[98] have been notably successful in generating large amounts of health data that either point to health outcomes directly (e.g., mortality and morbidity data),[99] or which can be analysed to map health outcomes (e.g., disease-specific data, civil registration data and child health data, among others). [100] This in huge part because data collection by CHWS draws on a variety of data sources beyond routine facility data, including community outreach, household visits and surveys.[101]

The success of CHISs has been enabled by the support of a wide range of stakeholders, including donors who fund the training of CHWs and civil society organizations have helped in developing the CHIS and training CHW on health data collection.[102] As AI adoption becomes more widespread, decentralised monitoring of AI impacts will be needed, and will similarly depend on extensive stakeholder support to succeed.

3.1.3 Introduction of technology and digital participatory surveillance

While many African health information systems still rely on paper-based tools, there has been increasing adoption of technology that has boosted health data collection, including collection of data on health outcomes.[103] Mobile technology, in particular, has been helpful in this, enabling collection of data even in rural and remote areas. In Tanzania, Malawi and Ghana, mobile technology has led to more accurate and timely reporting of morbidity cases of diseases like lymphatic filariasis by CHWs.[104] Though limited to a trial, SMS-reporting has been successfully used by CHWs in rural Ghana to report postpartum haemorrhage outcome data.[105]

Notably, mobile technology has also enabled digital participatory surveillance, which involves using digital tools to proactively engage community members in regularly reporting on health events and outcomes, thus complementing facility-based data sources.[106] The World Bank, for example, used mobile phone interviews with community members in Liberia and Sierra Leone to monitor the socio-economic impacts of the Ebola pandemic, including the pandemic's effects on labour markets, food security and education, among others.[107] Several African countries, including South Africa and Lesotho, have also piloted digital participatory surveillance programmes developed by the government and researchers respectively.[108] Though not designed to track health outcomes in particular, digital participatory surveillance is promising as it is cost-effective and allows patients to self-report health information through online systems, social media surveys, mobile applications, automated phone calls and texting.[109]

The successful use of technology and digital participatory surveillance in health data collection offers a valuable model for monitoring AI impacts, particularly in enabling cost-effective, scalable data collection from communities and individual users of AI. As AI adoption grows across Africa, similar digital tools and participatory approaches could be leveraged to collect data on AI impacts.

3.1.4 Investments in health journalism

Health journalists in Africa can play a key role in collecting health data, from noting rises in health cases to tracking vaccine distribution and healthcare innovations.[110] In doing so, health journalism can raise the profile of health issues, reveal deficiencies in healthcare services,[111] and prompt governments to collect more health information and implement corresponding policy.[112] Despite this potential of health journalism, however, health journalism in Africa has often been limited by insufficient editorial interest, limited understanding of health issues among journalists, pushback from health officers and governments, and inadequate funding.[113]

To address this, there has been growing support for health journalism that has boosted health data collection, often from external donor funding.[114] This has been through awards; professional networks such as the African Health Journalists Association and Health Journalists Network in Uganda;[115] professional training programmes like the Discover Centre for Health Journalism in South Africa;[116] and fellowships such as the Health Journalism Fellowship established by the Africa CDC with support from the World Bank, GIZ, and the European Union.[117] Health journalists at the Bhekisisa Centre for Health Journalism in South Africa, for example, have reported on maternal mortality in Sierra Leone, drawing on primary data they collected from a hospital in Sierra Leone.[118] Journalists in Kenya have similarly covered the dramatic reduction in postpartum haemorrhage rates in one county in Kenya.[119] The progress of health journalism offers some lessons in how to support technology journalism that aims to uncover AI impacts in African countries, as discussed further in section 4.3.

4 Recommendations on how to improve monitoring of AI impacts in African countries

The strategies that have strengthened health data collection in Africa offer instructive parallels for the monitoring of AI impacts. Drawing on these lessons, this section sets out four mutually reinforcing strategies: government-led monitoring and mandated reporting; decentralised monitoring by non-state actors; technology journalism; and digital participatory monitoring. Together, these strategies can build the evidence base African governments need to craft AI policy grounded in local realities. The recommendations are addressed to African policymakers, researchers, journalists, civil society and donors, and are designed to account for the diverse capacities and contexts across the continent.

4.1 Government-led efforts

African governments should take the lead on monitoring of AI impacts, especially because, as explained in section 2.2, they are the key beneficiaries of this data. Government-led efforts can fall under two categories: government-led monitoring and government-mandated reporting.

4.1.1 Government-led monitoring

African governments already collect massive amounts of data and statistics on various socio-economic indicators, through national statistical offices[120] and ministries.[121] This existing state apparatus can thus be leveraged to collect robust data on the impacts of AI. This subsection first considers the different state actors that can contribute to AI impacts monitoring, before turning to broader considerations, including the need to decentralise monitoring to reach rural and remote areas and the need to calibrate monitoring to different levels of state capacity.

Starting with the relevant state actors: ministries are well-placed to monitor the impacts of AI adoption in the sectors they oversee. The existing work of some ministries suggests that their mandate could be expanded to include systematic monitoring of AI impacts. Several ministries of education, including in Rwanda and Mauritius, collect data on the use of Information and Communication Technology (ICT) in schools, including the number of schools that use ICT in teaching and learning, the number of schools that have internet connectivity and smart classrooms, among others.[122] This is also the case in several ministries of agriculture. In Kenya, the Ministry of Agriculture and Livestock Development collects agriculture data and statistics, including on access to and use of ICT tools by farming households.[123] The Rwandan Ministry of Agriculture & Animal Services similarly tracks digitalization in the agricultural sector and the impact of the various tools and systems used.[124] These data collection efforts could be extended to include how AI is being adopted in these sectors and the impacts of such AI adoption. Various other ministries can also add an AI component to their data collection efforts.

National statistical offices and ministries of ICT such as in Rwanda and Zimbabwe also collect statistics on ICT use in specific sectors and could therefore assist in monitoring sector-specific AI impacts as well.[125] In addition to this, national statistical offices and ministries of ICT can collect data on AI impacts that are not sector-specific, as they already collect data on ICT broadly. Several ministries of ICT and national statistical offices across the continent, including the Mauritius Statistical Office,[126] the Rwandan Ministry of ICT and Innovation,[127] and Statistics South Africa,[128] routinely collect data on ICT access and use by individuals and/or households generally, and could thus extend their data collection to data on AI usage by individuals and the impacts from such use. Some national statistical offices collect even more granular data. For example, the Kenya National Bureau of Statistics collects information on various online risks such as online abuse, online impersonation, online fraud, phishing and Botnet/DDos Attacks.[129] Collection of data on AI incidents such as on cyberoffense and AI-enabled information risks (e.g., misinformation and deepfakes) can thus be added to its work.

Importantly, the national statistical offices or ministries of ICT can establish specialised alternatives for collecting AI impacts data. For example, as national 'agencies or regulators' they can develop and maintain national AI incident databases,[130] which 'record, classify and analyse risks such as safety failures, biased outcomes, security breaches and malicious use'.[131] To comprehensively detect such failures, African governments can mandate monitoring and/or reporting of incidents from private entities, researchers and civil society, as is discussed in the next subsections.[132] Governments should also make these databases publicly available and encourage the public to report AI harms through such platforms and to specific regulators.[133] National human rights institutions can monitor and receive reports on human rights impacts, as the Nigerian Human Rights Commission plans to do, for example.[134] Data protection authorities can track AI harms related to privacy and personal information,[135] while consumer protection and competition authorities monitor AI's impacts on consumer rights.[136] Cybersecurity agencies, in turn, can monitor cyber-related impacts.

Finally, labour ministries and agencies can monitor AI's impacts on labour and productivity across sectors and industries, in collaboration with national statistical offices. This can be done by adding an AI component to labour surveys, for example. Noting the impact of ICT on labour indicators such as productivity, some national statistical offices like the Uganda Bureau of Statistics,[137] already collect data on ICT access and usage in their labour surveys. Data on AI usage can be analysed with other data on labour indicators collected such as data on job losses. In Uganda, for example, the Ugandan Bureau of Statistics collects information on job losses and the reasons for the job losses, which could be useful in monitoring AI's impacts on employment.[138] Ultimately, these state actors should constantly communicate and coordinate with each other to avoid duplication of efforts, as has often happened in health information systems.

Crucially, these state actors should broaden their monitoring of AI impacts to more rural and remote areas and not just urban areas, as demonstrated by health data collection. Countries which see more widespread diffusion, such as in rural and remote areas, will need decentralised monitoring to cover these areas. This level of diffusion is to be expected in some countries because of increased AI adoption in certain sectors of the economy. Most agricultural activities in Africa are concentrated in rural areas,[139] for example, and AI agricultural solutions are thus likely to diffuse to these rural areas. Similarly, AI solutions are being designed for application in rural health settings and to expand access to education in rural and remote areas.[140] Countries which realise this level of diffusion thus ought to account for AI impacts in these areas, and invest in decentralised data monitoring.

Finally, monitoring of AI impacts will be greatly dependent on state capacity, including in the capacity to collect and analyse data that is required for decision-making, which varies among African countries.[141] Statistical capacity differs on many levels,[142] including data sources,[ix] data products,[x] and data infrastructure.[xi] World Bank data illustrates the disparity among African

ix Data sources refer to the various types of sources that are generated by the statistical system such as censuses and surveys, among others.

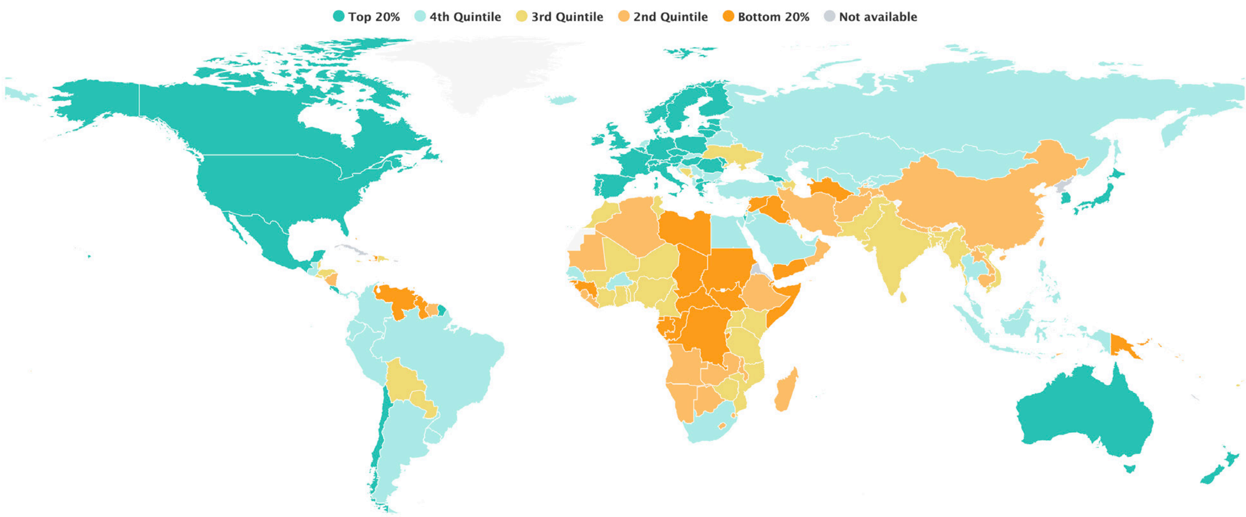
x Data products refer to the category of data or statistics generated by a statistical system and include the social, economic, environmental and institutional statistics.

xi Data infrastructure refers to the capability of a statistical system, including the skills within the system, and finance that is mobilized.

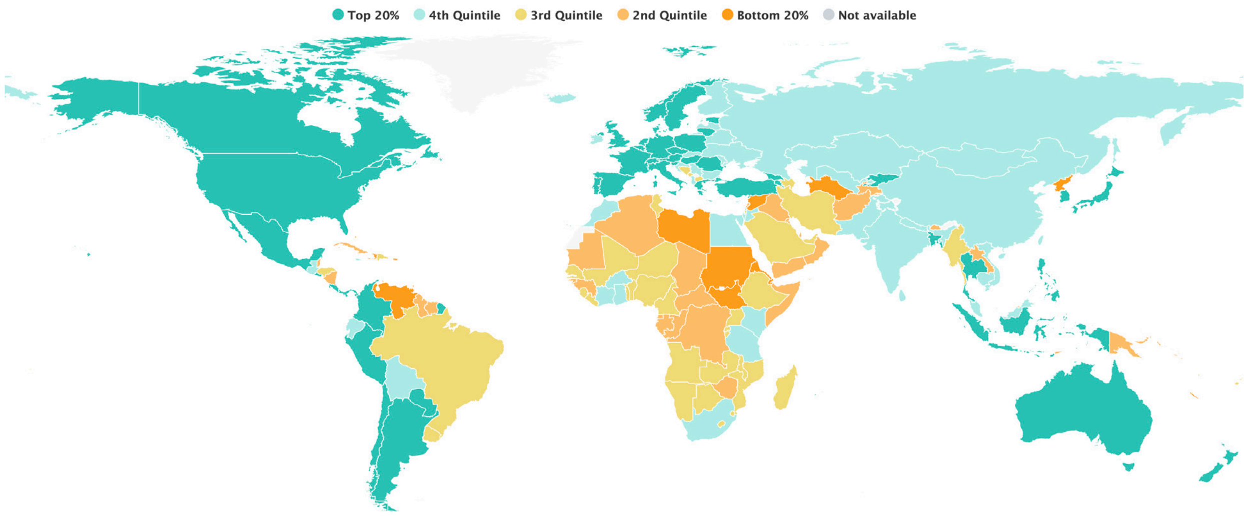
countries along all these lines.

High-capacity countries, for the purposes of this report, refer to countries that rank highly on most of these indicators, including South Africa, Mauritius, Burkina Faso, Senegal and Egypt. Medium-capacity countries are those that rank medium on most indicators and high on others, or generally medium across all indicators. These include Botswana, Ghana, Kenya, Nigeria, Malawi, Togo, Uganda and Zambia, among others. Finally, low-capacity countries are those that rank lower on most of these indicators including Burundi, Chad, the Democratic Republic of Congo and Somalia, among others.

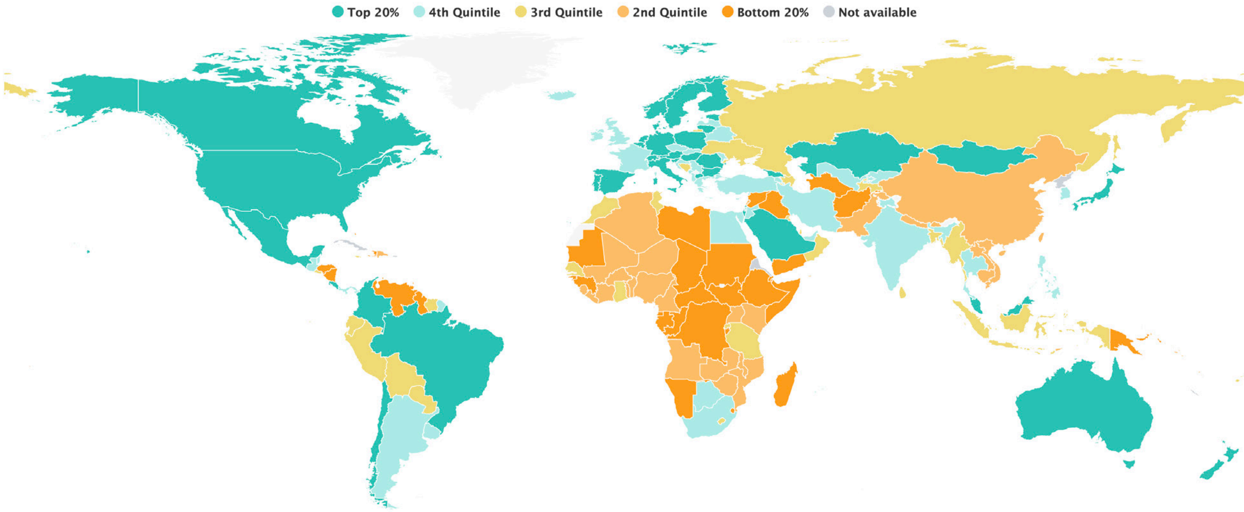
World Bank Overall Ranking for the year 2024.[143]



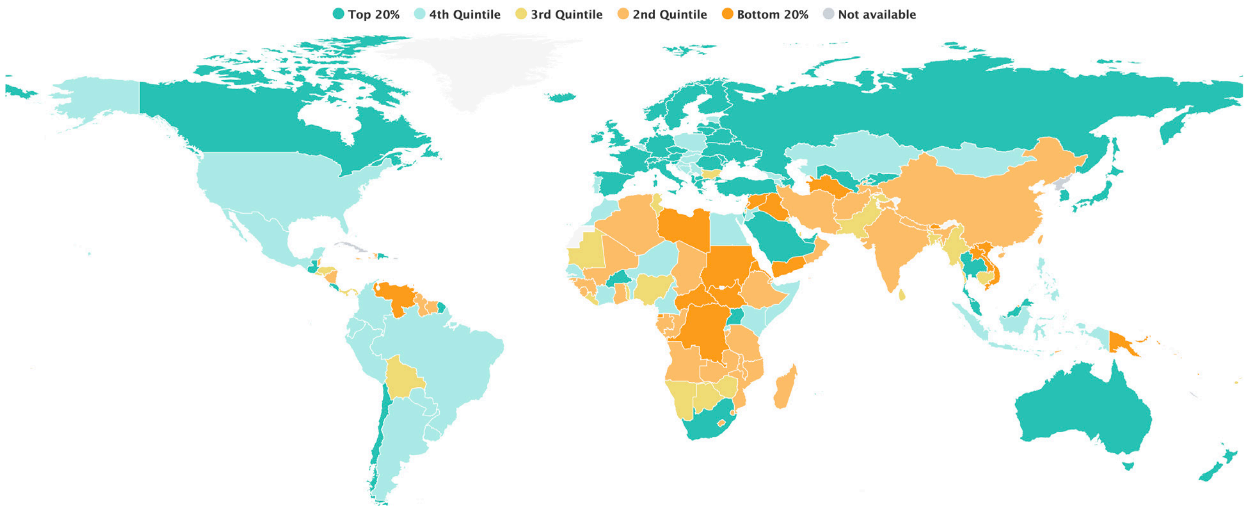
World Bank ranking on data products for the year 2024.[144]



World Bank ranking on data sources for the year 2024.[145]



World Bank ranking on data infrastructure for the year 2024.[146]



High-capacity and medium capacity countries with reliable statistical systems can draw more extensively on their established systems and methods to collect and analyse AI impacts data. Given their greater capacity to collect more data from more sources and generate more data products, they can collect data on AI impacts across many sectors and from more entities. They can, for example, add an AI component into a number of existing surveys such as agriculture surveys, labour force surveys and business surveys, and other sources. Based on their better data infrastructure (especially, skills and finances), these countries may also be better equipped to monitor the impacts that are not directly observable, as discussed in section 2.1.1. These countries can rely on their own expertise and finances to conduct analysis and research that links data from a variety of sources to uncover these AI impacts. Importantly, their financial and human resource capacity can also be extended to establishing new dedicated tools and offices such as AI incident databases and other alternative localised reporting mechanisms.

Low-capacity countries may be more constrained fiscally, infrastructurally and in personnel, and thus need to adjust their monitoring to their strengths. Some low-capacity countries may have extensive capacity when it comes to specific sectors and data sources and can start there. For example, the Republic of Congo[147] has consistently conducted agriculture surveys and can thus begin by adding an AI component to such surveys to measure AI impacts in the agricultural sector. As these countries improve their statistical capacity to more data sources and data products, they can then extend their monitoring to more AI impacts, across more sectors. Low-capacity countries can also seek to collaborate with non-state actors detailed in sections 4.2 on a greater scale, to bolster their data collection efforts. For example, they can collaborate with researchers to monitor impacts that need more analysis and research. Such collaborations can 'provide the technical and financial support needed to develop robust data systems and build local capacity for data collection and analysis'.[148]

Ultimately, all African governments will need to invest more in their statistical capacity, and especially so for impacts which require more detailed and empirical analysis. They should also collaborate with non-state actors detailed in section 4.2.

4.1.2 Government-mandated reporting

African governments can supplement their monitoring efforts with reporting from developers and deployers of AI as well as other actors like private entities, civil society and researchers who might have AI impacts data as explained in section 4.2.

First, African governments can require post-deployment monitoring and incident reporting from companies whose models are adopted across their jurisdictions. Other regimes such as the EU AI Act and California's SB 53 have already set the pace for such requirements.[149] Enforcing such schemes will be challenging,[150] but more so for African countries due to their limited regulatory capacity, particularly, the institutional and resource capacity needed to maintain a reporting regime.[151] However, these requirements can be tempered — for example, by only requiring reporting of incidents of certain magnitude or severity and adjusting the timelines of reporting according to the severity.[152] Requiring reporting from these companies can supply AI impacts data to the governments.

Second, African governments can also collect data that enables tracing of AI systems and models that are adopted in their jurisdictions. This data can then guide African governments and other actors (as detailed in the subsequent subsections 4.2., 4.3 and 4.4), on the adoption contexts where monitoring of AI impacts should be focused. Here, there are two categories of data that African governments need to acquire: (i) country-level data on AI usage from AI developers and (ii) data on the use and intended use of AI.

Country-level data on AI usage can help African governments know where to monitor for AI impacts in their jurisdictions by denoting where and how AI is being used. This data can be linked with other socio-economic indicators to comprehensively capture the effects of AI. For example, it can be linked with data on employment and hiring to evaluate the labour impacts of AI.[153] As such, collecting this data would be a crucial starting point for African countries in monitoring AI impacts.

AI developers usually hold this more granular usage data like breakdowns of who uses their models (breakdowns by industry (jobs) and demographic) as well as how their models are used (breakdown by tasks and topics).[154] There have been proposals about how governments like the United States (US) government should get this data and use it to ascertain the AI's impact on labour. These proposals suggest data-sharing partnerships with private-sector AI developers, and suggest modelling the initial reporting format on Anthropic's Economic Index.[155] African countries can also start pursuing such data-sharing partnerships. Where African countries face challenges establishing such partnerships due to power asymmetries with foreign AI companies,[156] they can lead or join multilateral efforts to get AI companies to share this data regularly. Frontier AI companies have committed to 'advancing understanding of real world AI usage' as part of the New Delhi Frontier AI Commitments emanating from the India AI Impact Summit.[157] Building on this commitment, African countries can lead or join collaborative efforts to encourage AI companies to share anonymised country-level data on how AI is deployed across sectors.

Finally, African governments can also require disclosure of use (and intended use) of AI especially if there is potential for harm to occur.[158] Other jurisdictions, like the EU and the US, already require such disclosures. The EU AI Act, for example, 'requires providers of high-risk systems to register in a public database before deployment', while US 'federal agencies are required to establish and annually update public-facing AI use case inventories of their AI current and planned deployments'.[159] For African countries, the implementation of such a framework will also depend on the level of AI adoption and regulatory state capacity. As AI continues to be adopted widely, it might be cumbersome to register every single instance of use or intended use. As such, African governments can require disclosure of adoption in 'high-stakes domains'.[160] These include uses (i) likely to impact many people, especially uses which people cannot opt out of such as the use of AI in the public sector,[161] and (ii) in sensitive areas such as health, education and critical infrastructure as the EU has done, for example.[162] Governments with more capacity can tweak these conditions as they see fit, to accommodate more disclosures of uses and intended uses. Governments can also adjust the type and amount of information they request about the models and systems according to their capacity.[163]

Reporting requirements will also need to take into account other interests that may be implicated, such as user privacy and the companies' legal obligations to its customers,[164] as well as the companies' own privacy concerns and trade secrets.[165]

4.2 Decentralised monitoring by non-state actors

It is also critical to decentralise monitoring of AI impacts from governments to non-state actors. Decentralisation in this manner will ensure that any gaps in government-led monitoring are filled in by non-state actors-led monitoring. Importantly, this can ensure that the impacts of government use of AI are also monitored and documented. Non-state actors who could be instrumental in this way include independent researchers, research organizations, civil society organizations (CSOs) and non-governmental organizations (NGOs).

Some researchers and research organizations already conduct research on the impact of technology on African communities and systems. They include organizations and individuals that work on advancing or reporting on digital rights and issues such as surveillance and disinformation, among others.[166] The African Digital Rights Network (ADRN), for example, has produced comprehensive documentation of digital surveillance across the continent, including studies of facial recognition technology, biometric digital-ID systems, and their impacts on citizens' rights in countries including Kenya, Malawi, Nigeria, South Africa, Zimbabwe and Zambia.[167] This network could extend its work to systematic documentation of AI impacts on digital rights. Additionally, centres like the Centre for Intellectual Property and Information Technology Law (CIPIT), which track the state of AI in Africa annually, could extend their work to researching and documenting the impacts of AI.[168] Finally, sector-specific researchers and research institutes such as in agriculture, healthcare, education and economics can also be a useful avenue to complement monitoring by ministries.

These researchers can conduct research to trace and document AI impacts, including field research that directly generates AI impacts data. They can also conduct more analytical research, drawing from data collected by other players like governments on AI usage and other socio-economic indicators to establish the more complex AI impacts like systemic labour impacts.[169] The researchers can also establish their own incident tracking and monitoring databases, in the manner that researchers at the Massachusetts Institute of Technology (MIT) and civil society elsewhere have done,[170] and develop other technological tools and accessible reporting channels[171] to support reporting of AI impacts as detailed in section 4.4. Other non-state actors like civil society organisations and NGOs, can advocate for transparency from governments and other non-state actors on AI adoption,[172] in order to support monitoring of AI impacts by researchers and civil society organisations.

Donor funding can be instrumental in supporting these monitoring efforts, as well as government-led efforts. There are already initiatives funding this kind of research such as the Africa Innovation Mradi Research Grants,[173] and International Development Research Centre (IDRC) and the United Kingdom's Foreign, Commonwealth and Development Office (FCDO), through the Artificial Intelligence for Development (AI4D) Programme.[174] Drawing lessons from health data collection, donor funding should be extremely careful not to fragment monitoring of AI impacts. Where feasible,[xii] support should be designed in a way that enables collaboration between governments and non-state actors. In some instances, for example, non-state actors might find it useful to collaborate with ministries or statistical offices to investigate some impacts of AI and funding should support such collaborative efforts.

4.3 Technology journalism on AI impacts

One other set of non-state actors that can support monitoring of AI impacts in Africa is technology journalists. News reports on AI impacts, like in health, can help raise awareness and prompt government response. Furthermore, like all other non-state actors discussed in section 4.2., technology journalists can be instrumental in checking government use of AI, in line with the media's role as 'a cornerstone of democratic governance in promoting transparency, accountability and the rule of law within society'.[175] Finally, data from news reports can also complement other monitoring efforts such as incident databases. Already, news reports are feeding into incident trackers, like the Organization for Co-operation and Development (OECD)'s AI Incidents and Hazards Monitor (AIM), which 'detects AI incidents and hazards from reputable international news outlets'.[176]

However, technology journalists in African countries, like health journalists, may face a myriad of challenges such as inadequate funding, personnel and knowledge. This is likely to be the case for a technical topic like AI. Substantial investment in these resources is thus needed to boost monitoring of AI impacts, by enabling the upskilling of journalists to understand how AI works and thus accurately report on the impacts, and by increasing journalists' coverage, including enabling them to investigate the impacts in remote areas.

Donors seeking to support monitoring of AI impacts through technology journalism can support three categories of journalists, namely investigative journalists, digital media journalists and community-based media. Supporting digital media journalism is promising for two reasons. Digital media has increasingly been driving social and political change indicating its potential to produce news on AI impacts that drives evidence-based AI policymaking.[177] Furthermore, digital media journalists have increasingly been reporting on places that are largely underreported,[178] hence would be a good way to decentralise monitoring, particularly for countries where AI adoption is characterised by 'great' diffusion within the country. Supporting community-based or local media may also be a promising avenue to collect data in remote areas. On the other hand, investigative

[xii] It might not be desirable to require or encourage collaboration where the impacts being monitored are from government use or adoption of AI, for example. Here, independent monitoring might be more desirable.

journalism, whether in traditional media or digital media, ordinarily aims to expose problems in society,[179] and may thus be suitable for collecting information on AI harms.

Donors may also choose between various ways to channel this funding, with one promising avenue in African countries being journalism fellowships. Journalism fellowships are suitable for donors who want to offer financial support as well as non-financial support like mentorship and training sessions to journalists.[180] These fellowships can be established and supported by a variety of actors, who can act independently or in collaboration. These actors include philanthropic donors, independent research and media centres and organizations, governments and intergovernmental organs.

Donors, for example, may channel their funding through trusted media centres and organizations. Luminate, a philanthropic firm, has already supported the Centre for Journalism Innovation and Development (CJID), in launching the AI and Tech Accountability Reporting Fellowship to support reporting of the societal impacts of AI in Africa. Notably, this fellowship includes training for the participants on the topics such as how AI is developed and deployed and how AI systems function.[181] There are many more reliable media organizations in Africa such as the Media Institute of Southern Africa, the Media Foundation for West Africa, Collaboration on International ICT Policy for East and Southern Africa (CIPESA) and Africa Centre for Media Excellence (ACME) which donors can collaborate with in establishing such journalism fellowships.[182]

At the intergovernmental level, the African Union can also seek to support technology journalists. The AU has previously launched journalism fellowships, including the Africa Media Fellowship,[183] and has already recognised the need to gather information on the socio-economic as well as security impacts of AI in Africa.[184] As such, the African Union High Level Panel on Emerging Technologies (APET) could establish a fellowship to support technology journalists in reporting on AI impacts in Africa.

4.4 Digital participatory monitoring of AI impacts

Altogether, African governments and non-state actors monitoring AI impacts, as well as donors, can invest in digital participatory monitoring to boost and actualise monitoring efforts. This will involve providing reporting channels such as online systems enabled by the internet, mobile applications and social media surveys, like in health data collection, to individuals and organisations that have information on AI impacts. These individuals and organisations could be the affected parties or third-party individuals and organisations.[185] Digital participatory monitoring can help increase the coverage of AI impacts monitoring, including by enabling collection of the details on AI impacts that are spread between many different parties, as discussed in section 2.1.2.

Implementing digital participatory monitoring will need to account for some contextual realities in African countries. First, digital participatory monitoring is hugely dependent on connectivity, including access to gadgets such as mobile phones, and for some, access to the internet. Therefore, any efforts in this respect need to be tailored to the African connectivity context. While internet connectivity and mobile connectivity of Africans continue to grow, many Africans still lack access to either or both.[186] Furthermore, access differs greatly across and within African countries,[187] with South Africa, for example, having 74.7% penetration in 2024 while other countries such as Chad and Central African Republic had penetration rates below 15%.[188]

To collect AI impacts data from individuals and organizations that easily have access to the internet and electronics, those monitoring AI impacts can develop open submission models like what the OECD is developing to add to its AI incident tracker to complement AI incidents from news reports,[189] and some other AI incident trackers have.[190] In these open submission models, stakeholders who interact with AI can self-report AI impacts such as AI incidents, and thereafter actors monitoring AI impacts can analyse these reports. Importantly, such models could be scalable and allow collection of data from a wide pool of stakeholders including individuals, organizations and even sector-specific stakeholders such as healthcare facilities. It would also be very useful in collating data incidentally collected by other bodies in the course of their functions. For example, regulatory bodies like Data Protection Agencies, tribunals and courts may have information on effects such as bias, discrimination and privacy infringements, among others, which could be collated using these digital platforms.[191]

To collect AI impacts data from individuals and organizations with limited access to the internet, actors monitoring AI impacts can leverage the expanding access to mobile phones in Africa. This is especially in countries such as South Africa, Kenya, Mauritius and Botswana with high mobile connectivity.[192] There are already existing local tools such as Ushahidi which have been used extensively in different African countries to get citizens' thoughts and feedback on a number of issues.[193] In Zimbabwe, for example, Ushahidi has been used by a peacebuilding organization to help citizens report human rights violations anonymously.[194] In this and other deployments, Ushahidi has enabled participatory data collection through zero-rated SMS, allowing individuals to report issues without incurring any costs and without need for internet connectivity.[195]

Second, sustaining digital participatory monitoring requires public engagement. In health, for instance, European countries have sustained participation through media campaigns and public health messaging.[196] Similarly, the National Institute for Communicable Diseases of South Africa invested in a public relations and media strategy.[197] Similarly, to get reliable and useful reports from the public on the impacts of AI, it might thus be useful to conduct public education on AI and what impacts the public should report. NGOs, researchers, research organizations and any other actors intending to use participatory monitoring can lead this as part of their monitoring projects. Furthermore, these efforts will need to leverage tools that are easy to use and interact with, such as tools fitted with local languages,[198] and perhaps tools that Africans are familiar with. For example, where possible, actors monitoring AI impacts can leverage tools such as WhatsApp and social media to conduct surveys.[199]

Lastly, considerations of privacy and data protection are likely to be key for stakeholders such as healthcare facilities, private organizations and even regulatory agencies, hence need to be accounted for in the design of these models. Government agencies may thus have to take the mantle and establish their own open submission models for collecting reports which may contain sensitive elements.

5 Conclusion

As AI adoption accelerates across Africa in critical sectors and among individual users, African policymakers are developing strategies and frameworks to govern AI. However, they are doing so without a critical type of evidence needed to make informed decisions. This report has argued that AI impacts data can close this evidence gap and serve other important purposes. It has offered four mutually reinforcing recommendations to that end, including government-led monitoring and mandated reporting, decentralised monitoring by non-state actors, technology journalism, and investment in digital participatory monitoring. Together, these strategies can build the evidence base that African governments need to craft policies that reflect the lived realities of their citizens.

This report should be understood as a preliminary response to a complex challenge. Implementing the recommendations outlined here will require additional research and experimentation. One immediate priority is the development of practical tools that can enable systematic monitoring of AI harms and impacts across diverse sectors. Encouragingly, early initiatives in this direction are already emerging. For example, the Centre for AI Security and Access has recently launched a prize to support the development of tools that can facilitate monitoring of AI-related harms.[200]

Further research is also needed to build a more granular understanding of the capacity of African countries to monitor AI impacts, and how this can be improved. This report has drawn broad distinctions between higher-capacity and lower-capacity countries, noting that the variation in statistical capacity is a key factor in designing feasible and proportionate monitoring systems. More granular studies of national data systems, regulatory institutions and research ecosystems would help identify where gaps currently exist and what kinds of interventions may be most effective in different contexts. Such research should assess not only data infrastructure but also analytical capacity, including the ability of governments and research institutions to interpret data and establish causal relationships between AI adoption and observed socio-economic outcomes.

Taken together, these areas of future research underscore that building robust monitoring systems for AI impacts will be a long-term and collaborative endeavour. Governments, researchers, civil society organisations, journalists and other partners will all play a role in developing the institutional, technical and analytical capacity required to track AI's evolving impacts. Strengthening this capacity will not only support more informed policymaking within African countries but will also enable the continent to participate more meaningfully in global efforts to govern AI.

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