Talent Landscape Mapping & Pathways for the African AI/LLM Language Models Initiative

Workstream: Talent Workstream

Lead Organisation: GSMA

Prepared by: Smartech Global

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Foreword

The GSMA convened the African AI Language Models Initiative to assess and strengthen the continent's capacity to build language models that reflect African languages, cultures and user needs. This report presented the findings of the Talent Workstream's mapping exercise and pathway design effort, which informed the Initiative's pan-African pilot programme and MWC outreach.

The research adopted a mixed-methods approach: a structured expert survey provided baseline quantitative data, semi-structured interviews offered qualitative validation and context, and secondary labour-market and sector data supplied corroborating evidence. We applied an explicit prioritisation method — combining expert-rated importance and availability — to identify urgent skill gaps and to rank training needs. The work was guided by clear, Africa-led principles and rapid, practical timelines to ensure outputs were actionable for pilots and employer partners.

The report achieved three practical outcomes. First, it produced a continental talent map showing where seven core skill clusters were concentrated and where shortages existed. Second, it identified a ranked set of priority skill gaps that required immediate attention. Third, it delivered short, implementable talent pathways (including suggested partners, time-to-job metrics and resource needs) intended for rapid piloting and employer validation.

By documenting what existed, what was missing, and how to close the most urgent gaps, this report supported the Initiative's aim of ensuring that African language AI is built by African talent for African users — and provided a clear set of next steps for GSMA partners, employers and training providers.

— GSMA Leadership

Acknowledgements

This report was made possible through the collective expertise, collaboration, and institutional support of numerous stakeholders across the African AI ecosystem.

We extend our sincere appreciation to the GSMA Coordination Team for providing overall strategic leadership, programme governance, and operational oversight throughout the research. Their guidance ensured clarity of direction, methodological rigor, and alignment with broader ecosystem objectives.

We are deeply grateful to the Talent Workstream Leads and Co-Leads, whose insights were instrumental in shaping the skills framework, refining the analytical methodology, and validating the practical relevance of the findings. Their stewardship strengthened both the conceptual foundation and applied value of the report.

Special recognition is also due to the Architects, whose technical and analytical expertise significantly enhanced the design of the skills mapping framework and the development of pathway templates. Their contributions ensured that the approach was robust, scalable, and grounded in industry realities.

We further acknowledge the invaluable contributions of representatives from laboratories, universities, innovation hubs, companies, and independent experts who participated in surveys and interviews. Specifically, this project received invaluable contributions (empirical insights) from Masakhane African Languages hub (Kenya), Novation City (Tunisia), SDAS Research Group (Morocco), RalphAI (Ghana), Bloom Academy For Artificial Intelligence (BAFAI) (Nigeria), University of Pretoria/ Deep Learning Indaba/ Deep Learning IndabaX (South Africa), BV lab (Morocco), 10 Academy (Ethiopia), DevisionX (Egypt), Chad Innovation Hub (Chad), Save Your Wardrobe (Tunisia). Their perspectives, data inputs, and contextual insights enriched the empirical depth and practical relevance of the analysis.

Finally, we thank the GSMA G6 (Africa Group of Six)—Airtel, Axian, Ethio Telecom, MTN, Orange, and Vodacom—and our ecosystem partners, as well as other partner organisations that supported stakeholder mobilisation, facilitated access to critical data sources, and contributed to validation processes. Their collaboration was essential to the credibility and completeness of this research.

The successful completion of this report reflects the shared commitment of all these contributors to advancing Africa’s AI talent ecosystem.

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Executive Summary

Purpose

Artificial Intelligence (AI) is rapidly becoming a critical driver of digital transformation and economic competitiveness worldwide. As governments, industries, and research institutions increase investment in AI technologies, the availability of skilled talent capable of developing, deploying, and governing AI systems has become a strategic priority. Across Africa, interest in AI has grown significantly in recent years, yet there remains limited consolidated evidence on the structure and capacity of the continent's AI talent ecosystem. This research was conducted to map the **African AI talent landscape**, with the aim of understanding where AI talent is produced, where labour market demand is emerging, and which skills are most critical for the development of sustainable AI ecosystems. The research provides evidence-based insights to support policymakers, industry leaders, academic institutions, and development partners seeking to strengthen Africa's AI capabilities.

Methodology

The research combines **secondary data analysis, expert surveys, and qualitative interviews** to provide a comprehensive assessment of Africa's AI talent ecosystem. Three key dimensions of the ecosystem were analysed. First, **AI labour market demand** was examined using job posting data to identify geographic demand patterns and priority skill clusters. Second, **AI knowledge production** was analysed through academic publication data to assess the scale and distribution of AI research activity across the continent. Third, **technical capability production** was evaluated through GitHub repositories, capturing open-source development activity among African AI developers. These quantitative analyses were complemented by **expert surveys and interviews with AI practitioners and ecosystem leaders across multiple African regions**, providing qualitative insights into talent development pathways, ecosystem challenges, and workforce priorities.

Key Findings: Strengths, Gaps, and Regional Patterns

- The findings reveal a **rapidly growing but uneven AI ecosystem across Africa**, characterised by strong innovation potential alongside significant structural imbalances.
- AI job demand is geographically concentrated. **North Africa accounts for approximately 37% of AI job postings**, followed by West Africa (21%), Southern Africa (20%), and East Africa (16%). At the country level, **South Africa, Morocco, Egypt, Nigeria, and Kenya together account for nearly two-thirds of total AI job demand across the continent.**
- AI research production has expanded significantly over the past decade. Total annual publications increased sharply after 2019, reaching **over 5,300 publications in 2025**, the highest level recorded in the dataset. Research output is concentrated in **Nigeria, Morocco, Ghana, South Africa, and Algeria**, while regionally **North Africa and West Africa jointly account for approximately 59% of total research activity**.
- Open-source AI capability production is also growing rapidly. Analysis of **more than 27,000 GitHub repositories** shows strong developer engagement across the continent,

particularly in West Africa, which contributes **over 53% of all repositories**. However, the distribution of technical capabilities is highly concentrated in **linguistic AI technologies**, which represent nearly **64% of all repositories**.

- A key structural insight from the research is the **misalignment between AI talent production and labour market demand**. Regions producing significant technical capability do not always correspond to those with the highest employment demand, indicating structural gaps in ecosystem development.

Top Priority Skills for Africa's AI Ecosystem

Across the different data sources and survey responses, five skill areas emerge as particularly important for strengthening Africa's AI ecosystem:

- **Evaluation and Quality Assurance**: Skills related to model validation, benchmarking, and performance assessment are currently underdeveloped but increasingly critical for responsible AI deployment.
- **Data Engineering for AI Systems**: Strong demand exists for professionals capable of building and managing large-scale data pipelines required for AI applications.
- **Applied AI Development and Deployment**: Practical expertise in integrating AI solutions into real-world products and services remains essential for scaling AI adoption.
- **Governance, Ethics, and Responsible AI**: Growing regulatory and societal concerns require stronger expertise in ethical AI design, policy frameworks, and risk management.
- **MLOps and LLMOps Infrastructure**: Operational skills for managing AI model deployment and lifecycle management remain limited across much of the continent.

Pathways for Developing AI and LLM Talent

The research finds that **no single training pathway is sufficient to produce job-ready AI professionals**. Instead, the most effective approaches combine multiple learning environments.

Universities continue to provide foundational technical education, but industry experts emphasise that **practical experience is essential for workforce readiness**. Project-based learning, industry apprenticeships, internships, and participation in open-source communities are widely viewed as the most effective mechanisms for developing applied AI capabilities.

Online learning platforms, technical bootcamps, and professional certifications also play a growing role in enabling rapid upskilling in emerging AI technologies.

Overall, the evidence suggests that **hybrid learning models that combine formal education with hands-on industry experience are the most effective pathways for developing AI talent across Africa.**

High-Level Recommendations and Next Steps

To strengthen Africa's AI talent ecosystem, the research identifies several strategic priorities;

- Invest in AI Infrastructure and Sovereign Compute Capacity
- Strengthen Industry–Academia Collaboration for AI Skills Development

- Expand Practice-Based AI Training Ecosystems
- Prioritise Development of Underrepresented AI Skill Clusters
- Support Open-Source AI Ecosystems and Developer Communities
- Implement AI Talent Retention and Global Talent Mobility Strategies
- Promote AI Solutions for African Societal Challenges

List of Abbreviations and Acronyms

AI – Artificial Intelligence

LLM – Large Language Model

AI/LLM – Artificial Intelligence / Large Language Model

UX – User Experience

UI – User Interface

UX/UI – User Experience and User Interface

CI/CD – Continuous Integration / Continuous Deployment

API – Application Programming Interface

MLOps – Machine Learning Operations

LLMOps – Large Language Model Operations

MLOps/LLMOps – Machine Learning Operations / Large Language Model Operations

NLP – Natural Language Processing

GSMA – Global System for Mobile Communications Association

SPSS – Statistical Package for the Social Sciences

PoPIA – Protection of Personal Information Act

JSearch – Job Search API Provider (via RapidAPI marketplace)

RapidAPI – API Marketplace Platform

GitHub – Web-based Platform for Version Control and Collaboration

Startups – Newly Established Companies

Telcos – Telecommunications Companies

NGOs – Non-Governmental Organizations

API Provider – Organization that Supplies Access to an Application Programming Interface

AI Systems – Systems powered by Artificial Intelligence technologies

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CHAPTER 1: INTRODUCTION

1.1 Background to the African AI Language Models Initiative

Africa is characterised by exceptional linguistic diversity, with over 2,000 languages spoken across the continent. These languages reflect rich cultural heritage, knowledge systems, and modes of communication, and they shape how communities access information, participate in governance, and engage with digital services. Despite this diversity, most African languages remain underrepresented in mainstream artificial intelligence (AI) systems, including large language models (LLMs) and other data-driven technologies.

This underrepresentation limits the usability, relevance, and inclusiveness of AI applications for African populations. AI systems are predominantly trained on high-resource languages, which reduces their effectiveness in local contexts, particularly in areas such as education, healthcare, public service delivery, financial inclusion, and digital entrepreneurship. As a result, large segments of African societies face barriers to fully benefiting from emerging AI innovations.

These challenges are compounded by persistent digital exclusion. Uneven access to reliable connectivity, limited computing infrastructure, scarcity of high-quality multilingual datasets, and shortages of specialised AI skills restrict Africa's capacity to develop, deploy, and scale indigenous AI solutions. These structural constraints reinforce reliance on technologies designed primarily for non-African contexts, which do not fully meet the linguistic, cultural, or socio-economic needs of the continent.

In response to these gaps, the GSMA launched the African AI Language Models Initiative to strengthen Africa's participation in the global AI ecosystem while prioritising local ownership and relevance. The Initiative has supported efforts to map existing skills, identify talent gaps, and design actionable pathways to build capacity across the continent. It fosters collaboration across four interrelated workstreams — Data, Compute, Talent, and Innovation & Market — to create an enabling environment for African-centred AI development.

The Initiative aims to support the development of language models that are more representative of African languages and contexts, promote capacity building among African practitioners, and stimulate innovation through partnerships with academia, industry, civil society, and government stakeholders. By addressing both technical and structural barriers, the GSMA Initiative seeks to advance a more inclusive, equitable, and sustainable AI future for the continent.

1.2 The Core Ambition

The core ambition of the African AI Language Models Initiative is to develop **AI language models in Africa, by Africa, and for Africa**, ensuring that AI technologies reflect the continent's linguistic, cultural, and socio-economic realities. This initiative addresses the persistent underrepresentation of African languages in AI systems and seeks to empower local communities, researchers, and developers to participate fully in the digital economy.

The Initiative operates under clear guiding principles. It is **African-led**, placing local expertise and decision-making at the centre of model development. It is **practical**, focusing on tangible outputs that can be deployed in real-world contexts. It is **market-relevant**, aligning skill development and AI solutions with the demands of African industries, public services, and innovation ecosystems. Finally, it is **scalable**, designed to extend its impact across multiple regions, languages, and sectors throughout the continent.

By combining these principles, the Initiative promotes an inclusive, sustainable, and locally grounded approach to AI development, aiming to reduce digital exclusion and strengthen Africa's position in the global AI landscape.

1.3 Purpose of the Talent Workstream

- Map existing AI/LLM skills
- Identify critical gaps
- Design actionable talent pathways
- Connect talent to pilots and real projects

The Talent Workstream focuses on mapping the current landscape of AI and large language model (LLM) skills across Africa. It aims to identify critical skill gaps that constrain the development, deployment, and localisation of AI technologies for African languages and contexts.

The Workstream seeks to design actionable talent pathways that enable learners and practitioners to acquire the skills needed to address these gaps. These pathways emphasise practical, job-linked learning, integrating formal education, industry-based experience, and project-based training.

In addition, the Talent Workstream connects talent to operational pilots and real-world projects, ensuring that skill development is aligned with market demand, innovation priorities, and African-centred AI initiatives. By linking capacity building with concrete applications, the Workstream strengthens the pipeline of qualified practitioners capable of advancing AI solutions that are relevant, inclusive, and sustainable across the continent.

1.4 Scope of the Report

The report covers the **Pan-African region**, encompassing all major geographic subregions of the continent, including West, East, Southern, North, and Central Africa. It examines the **current AI/LLM talent landscape**, while also considering a **10-year outlook** to inform medium- and long-term skills planning and capacity-building initiatives. The focus of the research includes three interrelated dimensions:

1. **Skills Mapping:** identifying existing AI/LLM capabilities, geographic distribution, and sectoral concentration of talent.
2. **Gap Analysis:** assessing critical skill shortages and areas requiring immediate attention to strengthen Africa's AI ecosystem.
3. **Pathways:** proposing actionable and scalable talent development pathways, including formal education, professional training, industry partnerships, and other capacity-building mechanisms.

By addressing these areas, the report aims to provide a **comprehensive, continent-wide assessment of AI/LLM talent**, highlight current opportunities and constraints, and inform strategic interventions for stakeholders across industry, academia, government, and civil society.

CHAPTER 2: PROJECT GOVERNANCE AND WORKSTREAM ARCHITECTURE

2.1 The Four Workstreams

The African AI Language Models Initiative is structured around four interrelated workstreams that collectively aim to build a robust, African-centred AI ecosystem. Each workstream addresses a critical component of the AI development pipeline and is designed to operate in coordination with the others to ensure systemic impact.

- **Data:** This workstream focuses on the identification, curation, and preparation of high-quality multilingual datasets. It ensures that African languages are adequately represented in AI training data, emphasising inclusivity, cultural context, and data quality standards.
- **Compute:** The Compute workstream addresses the infrastructure and computational requirements necessary to develop, train, and deploy large language models. It aims to increase access to scalable compute resources, optimise performance efficiency, and foster sustainable AI development practices across the continent.
- **Talent (focus of this report):** The Talent workstream concentrates on mapping current AI/LLM skills, identifying gaps, and developing practical pathways for African practitioners. It seeks to strengthen local capacity, build job-ready talent pipelines, and create opportunities for knowledge transfer between academia, industry, and research labs.
- **Innovation & Market:** This workstream ensures that AI solutions are effectively applied to real-world use cases and are commercially and socially relevant. It facilitates the integration of AI into products and services, evaluates market demand, and supports innovation pathways that connect AI capabilities with African industries, enterprises, and communities.

By operating in an integrated manner, the four workstreams create a comprehensive framework that advances Africa's capacity to develop, deploy, and scale language AI solutions that are locally relevant, socially inclusive, and technologically sustainable.

2.2 Roles and Responsibilities

The African AI Language Models Initiative operates through a clearly defined governance structure to ensure effective delivery of its objectives.

Leads and Co-Leads provide strategic oversight for the Talent Workstream, guiding the design of the skills mapping framework, validating methodological approaches, and ensuring that outputs are aligned with continental priorities and market needs. They coordinate across workstreams to maintain coherence and ensure that talent-related interventions integrate effectively with data, compute, and market activities.

Architects offer expert technical guidance on the design and implementation of the skills mapping and pathway frameworks. They are responsible for defining skill clusters, developing survey and interview instruments, advising on prioritisation methodologies, and providing analytical support for interpreting findings.

Contributors include representatives from laboratories, universities, innovation hubs, companies, and independent experts. They participate in surveys, interviews, and validation exercises, providing practical insights, empirical evidence, and regional perspectives that inform the Talent Workstream outputs.

The **GSMA Coordination Team** manages programme oversight, facilitates stakeholder engagement, and ensures adherence to timelines and deliverables. The team supports cross-workstream integration, liaises with partners and contributors, and maintains alignment with the broader objectives of the African AI Language Models Initiative.

Together, these roles ensure that the Talent Workstream operates efficiently, leverages expert knowledge, and produces actionable insights to strengthen AI/LLM talent development across Africa.

2.3 Guiding Principles

The Talent Workstream operates under a set of guiding principles designed to ensure that its activities are relevant, practical, and aligned with the broader goals of the African AI Language Models Initiative:

- **African-led decision-making:** All strategic and operational decisions are driven by African stakeholders, ensuring that priorities, methodologies, and outcomes reflect local contexts, needs, and expertise.
- **Evidence-based assessment:** Decisions, analyses, and recommendations are grounded in robust empirical evidence, including survey data, expert interviews, and secondary market intelligence.
- **Practical, job-linked outcomes:** Activities are designed to produce tangible, actionable results, including skills maps, pathways, and training recommendations that can be applied directly to workforce development and employment initiatives.
- **Fast, usable outputs for MWC Barcelona/Kigali:** The workstream prioritises timely delivery of outputs that are clear, actionable, and suitable for immediate presentation, validation, and adoption by stakeholders at key continental events.

These principles guide all aspects of the Talent Workstream, from survey design and skills mapping to pathway development and stakeholder engagement, ensuring relevance, credibility, and practical impact.

CHAPTER 3: CONCEPTUAL FRAMEWORK AND DEFINITIONS

3.1 Key Definitions

Skills Mapping refers to the systematic identification, documentation, and analysis of the current capabilities, competencies, and expertise of individuals or organisations within a given sector or geographic region. It highlights areas of strength, identifies gaps, and provides evidence to inform workforce planning, training interventions, and talent development initiatives.

Talent Map is a visual or analytical representation of the distribution of skills and expertise across regions, sectors, or organisations. It captures where critical competencies exist, the concentration of talent hubs, and areas where skills are scarce, providing a basis for strategic decision-making and resource allocation.

Skills Gap represents the difference between the skills required for a given role, function, or strategic objective and the skills currently available within the workforce or talent pool. Identifying skills gaps helps prioritise interventions, inform training programmes, and align talent development efforts with organisational and sectoral needs.

Pathways are structured routes through which individuals acquire the knowledge, skills, and experience needed to become competent in specific domains. Pathways may include formal education, industry-led training, fellowships, apprenticeships, online learning, project-based experience, or on-the-job development. Effective pathways link learning outcomes to employability and practical application.

Priority Score is a quantitative measure used to rank skill areas based on their strategic importance and current availability. It provides an evidence-based method to identify which skills require urgent attention and resource investment, thereby guiding decision-making in skills development and talent pipeline initiatives.

Table 1: Key Skill Clusters and Subsets

Skill Cluster	Definition	Key Subsets
1. Foundational AI/LLM Engineering	The core technical competencies required to design, develop, adapt, and optimise large language models and related machine learning systems.	• Model architectures and design (e.g., transformers, multimodal models) • Model training and fine-tuning • Inference optimisation and efficiency • Neural network implementation • Core ML engineering and algorithm development
2. Data Engineering for AI	Capabilities required to collect, process, manage, and prepare large-scale datasets for AI/LLM development, particularly in multilingual and low-resource language contexts.	• Data pipeline design and automation • Data cleaning and preprocessing • Multilingual data handling • Dataset curation and annotation infrastructure • Data storage, governance, and management
3. Linguistic & Cultural Expertise	Human knowledge and contextual understanding necessary to ensure that AI systems accurately represented African languages, meanings, and cultural nuances.	• Translation and interpretation • Language annotation and labelling • Native language proficiency and linguistic analysis • Cultural localisation and context interpretation • Community engagement for data collection
4. Evaluation & Quality Assurance	Skills required to systematically assess, validate, and improve AI/LLM performance, reliability, and fairness.	• Benchmark development • Model validation and testing • Bias detection and mitigation • Error analysis and debugging • QA frameworks for AI systems
5. Applied Product & Deployment	Practical capabilities needed to integrate AI models into real-world products, services, and user-facing applications.	• AI product development and lifecycle management • UX/UI design for AI systems • System integration and APIs • Human-in-the-loop design • Commercial and operational deployment
6. Governance, Ethics & Safety	Frameworks and practices required to ensure AI systems were developed and deployed responsibly, transparently, and in compliance with legal and ethical standards.	• Responsible AI principles • AI policy and regulation • Risk assessment and impact evaluation • Data privacy and security • Ethical review and accountability
7. MLOps / LLMOps	Operational and engineering capabilities needed to deploy, monitor, scale, and maintain AI/LLM systems in production environments.	• Model deployment and serving • CI/CD for AI systems • Model versioning and lifecycle management • Real-time monitoring and performance tracking • System reliability and scalability

3.3 Conceptual Model

The conceptual model illustrates the interconnections between skills mapping, talent maps, identified gaps, talent pathways, and priority scores, providing a structured framework for understanding the African AI/LLM talent ecosystem.

The conceptual model provided a structured framework for understanding how Africa's AI/LLM talent ecosystem functioned and evolved. It linked **Skills Mapping, Talent Maps, Gap Analysis, Priority Scores, and Talent Pathways** in a logical sequence: skills mapping identified existing and scarce competencies; talent maps visualised their geographic and sectoral distribution; gap analysis highlighted critical shortages; and priority scores guided the design of targeted talent pathways.

The model also depicted a dynamic, circular relationship between **Skills, Data, Compute, and Market Demand**. Skills enabled effective use of data and compute; data and compute supported further skills development; and market demand shaped the types of skills and pathways required. This continuous feedback loop ensured alignment between capacity building and real-world needs.

Aligned with the **Innovation & Market Workstream**, the model integrated technical, organisational, and market dimensions, ensuring that talent development priorities responded to practical industry opportunities while supporting long-term strategic planning for AI/LLM capabilities in Africa.

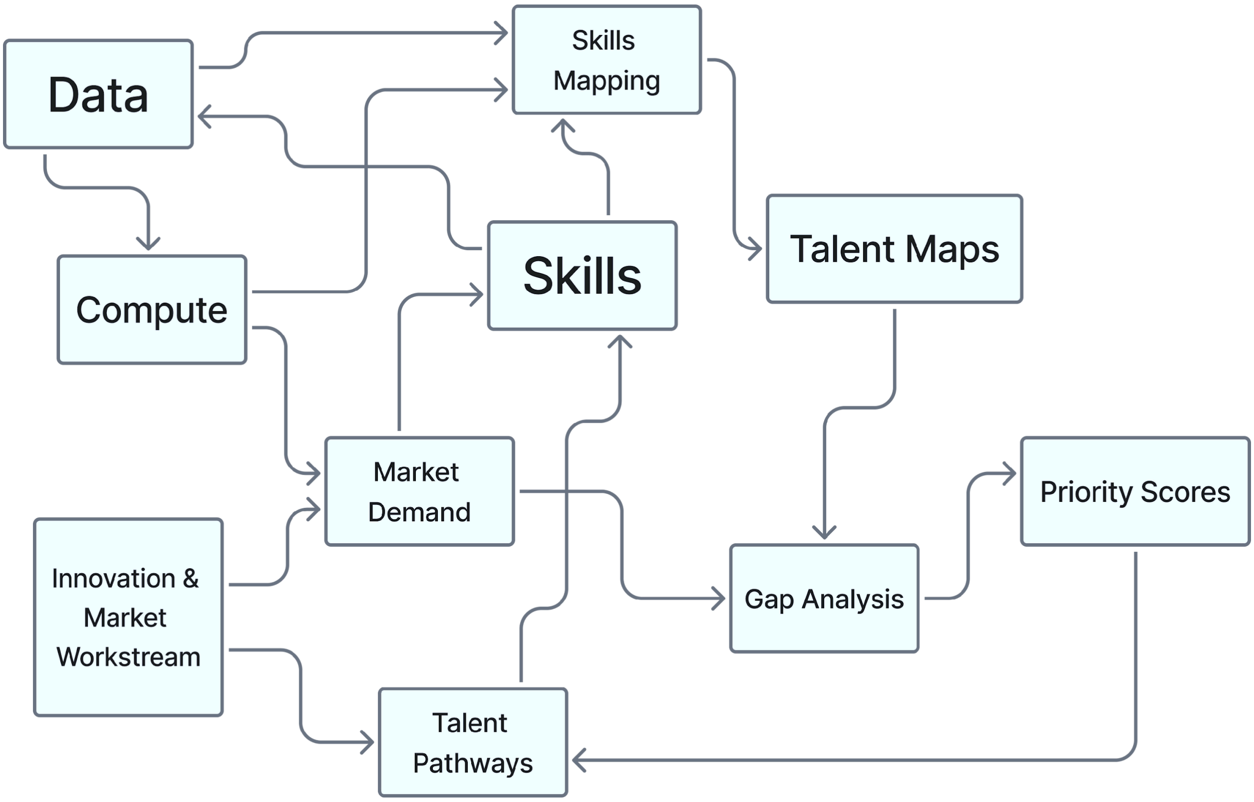
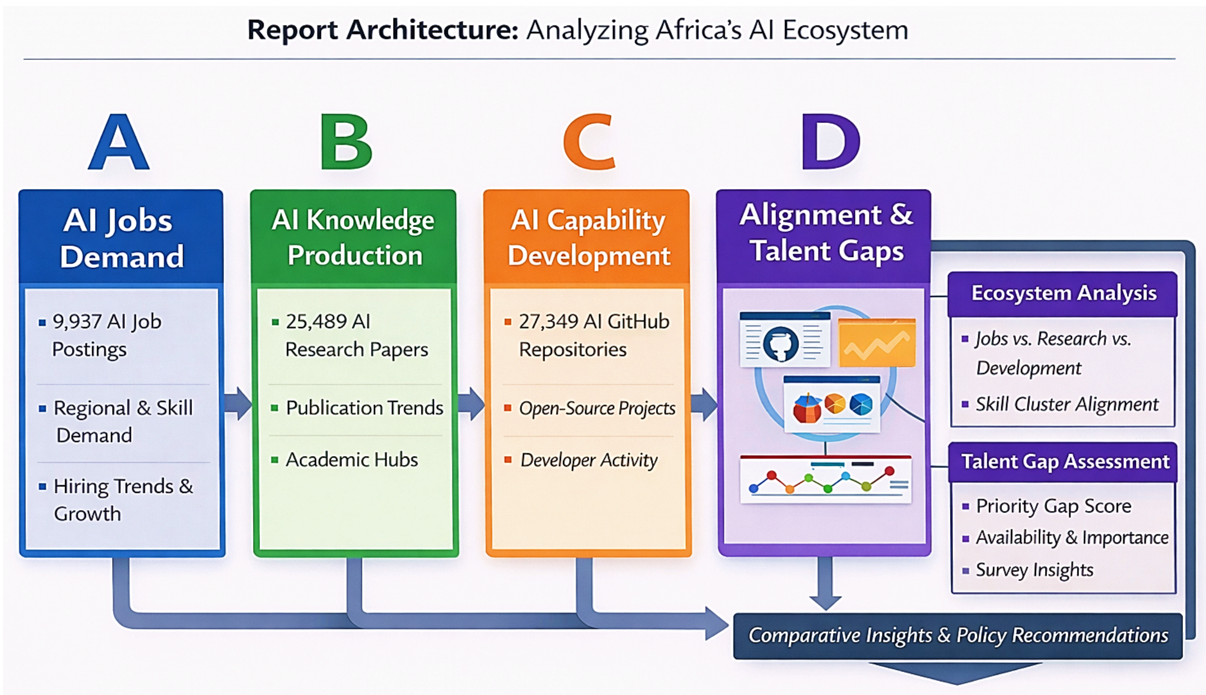


Figure 1: The conceptual model diagram, showing how skills mapping, talent maps, gaps, pathways, and priority scores interconnect



CHAPTER 4: METHODOLOGY

4.1 Research Design

The research adopts a mixed-method approach to assess the African AI/LLM talent landscape. It combines quantitative and qualitative data collection through an expert survey, semi-structured interviews, and secondary data sources. This approach enables a comprehensive understanding of existing skills, regional distribution, and capability gaps, while also capturing contextual insights from industry, academia, and research institutions.

The expert survey provides baseline quantitative data on the importance, availability, and geographic concentration of seven core skill clusters, offering a structured foundation for analysis. Semi-structured interviews supplement this with qualitative perspectives, enabling triangulation, validation, and the capture of practical observations and recommendations. Secondary data, including job market information, industry reports, and existing research on AI talent in Africa, contextualises the findings and supports a robust evidence base.

By integrating multiple sources of evidence, this research design ensures that the resulting skills map, gap analysis, and talent pathways accurately reflect both the current state of AI/LLM expertise in Africa and the opportunities for strategic intervention.

4.2 Data Collection Approach

The data collection approach is designed to capture a comprehensive and representative view of AI/LLM talent across Africa. It combines structured survey instruments, expert interviews, and secondary data to ensure triangulation and validity of findings.

4.2.1 Expert Survey Design

The research adopted a structured expert survey to establish a baseline understanding of AI/LLM skills across Africa. The survey was designed to capture quantitative data on the availability, importance, and geographic distribution of key skill clusters, and to inform the subsequent identification of priority gaps and talent pathways.

Target respondents included AI and LLM practitioners, research laboratories, universities, innovation hubs, industry representatives, and independent experts actively engaged in AI development or deployment across the continent. The survey instrument was structured into five sections (A–E), covering background information, skill cluster assessment, skills-to-pathways alignment, organisational upskilling programmes, and referrals and permissions.

For each skill cluster, respondents were asked to provide ratings on multiple dimensions, including current importance, future importance, availability, geographic spread, and confidence in their assessments, using a five-point Likert scale (1 = Very Low, 5 = Very High). The survey was administered online, allowing for voluntary self-completion and broad geographic reach, and a regional coverage strategy was applied to ensure balanced representation from West, East, Southern, North, Central, and Pan-African respondents.

The survey design ensured both **comparability across regions and skill clusters** and the collection of data that could be triangulated with interviews and secondary sources to produce a robust and actionable skills mapping and pathway analysis.

4.2.2 Expert Interviews

The report conducted expert interviews to complement the survey data and provide qualitative depth for triangulation purposes. The interviews were designed to validate the survey findings, clarify regional trends, and capture nuanced insights into skills availability, gaps, and talent pathways across African regions.

Interviews were conducted virtually, each lasting approximately 20–30 minutes. Participants included AI/LLM experts from laboratories, universities, innovation hubs, companies, and independent organisations, covering a broad geographic and sectoral representation.

The interview guide focused on four key thematic areas:

1. **Background of respondents** – roles, experience, and regional coverage.
2. **Skill cluster assessment** – importance, availability, geographic spread, and confidence in assessment across seven skill clusters.
3. **Talent pathways** – effectiveness of local and global training and upskilling programmes, and preferred approaches for developing AI/LLM skills.
4. **Ecosystem and demand** – sources of talent demand, skills shortages, retention challenges, and competitive dynamics.

Interviews were recorded with participant consent, and detailed notes were taken during each session. Thematic analysis was applied to identify recurring patterns, validate survey findings, and extract illustrative quotes to contextualise quantitative results. This approach ensured that the report reflected both measurable trends and expert perspectives on the African AI/LLM talent landscape.

4.2.3 Pre-Engagements with the Participants

Prior to formal data collection, the research team implemented a carefully sequenced pre-engagement programme designed to secure broad representation, improve response rates, and ensure that participants were fully informed and technically prepared for online survey completion and virtual semi-structured interviews. The process began with internal alignment on research objectives and the operational definitions of key constructs—such as AI talent, skills pipelines, ecosystem capacity, and language-model development—so that every outreach message and instrument reflected a consistent, clearly stated purpose aligned with the Initiative's strategic priorities.

With objectives clarified, the team constructed a purposive contact frame. Regional resource persons contributed initial lists and the team supplemented these through manual searches on companies' websites, Google, and LinkedIn to identify suitable organisational and expert contacts across African subregions. This compilation produced 333 targeted organisational contacts distributed across North, Southern, East, West and Central Africa (46, 34, 199, 22 and 32 respectively). Each contact was approached twice, resulting in a total of 666 outreach emails sent across the sample frame.

Email invitations were dispatched as part of a multi-channel recruitment strategy that also used the "Contact Us" portals on organisational websites, LinkedIn direct messages, and follow-up reminders where needed. To execute outreach at scale and maintain timeliness, the team automated the emailing process using Python scripts; this enabled rapid batch sending and consistent message formatting while preserving recipient-level customization. The team trialled a commercial email-campaign platform (Zoho) to compare delivery and tracking capabilities; however, that option was not pursued further after the account encountered restrictions that stalled campaign progress. Follow-up messages were issued selectively to clarify questions and to encourage survey completion and interview participation.

As respondents completed the online survey, those who indicated willingness to be interviewed received scheduling invitations and flexible time slots to accommodate diverse time zones and professional commitments. Confirmed interviewees were sent virtual meeting links together with brief preparatory guidance on the interview format, expected duration, and any technical requirements. Where necessary, the team checked participants' access to suitable hardware, software and connectivity to reduce the likelihood of interruptions during virtual sessions.

Concurrently, the survey instrument and interview guide were subjected to pre-testing and refinement. Draft materials were reviewed internally and piloted with a small group of individuals possessing profiles similar to target participants. Cognitive probing during pilot interviews exposed ambiguous wording and overly academic phrasing; iterative revisions reduced jargon, clarified terminology to reflect industry usage, and shortened items that risked respondent fatigue. These refinements improved question clarity, reduced respondent burden, and strengthened the instruments' practical relevance.

Ethical and consent procedures were integrated throughout the pre-engagement timeline. Prospective participants received advance information explaining the research's aims, intended uses of the data, confidentiality safeguards, and recording procedures. Electronic consent was obtained via the survey platform prior to data collection and verbal consent was reaffirmed at the start of each recorded interview. Treating consent as an ongoing, two-step process helped ensure that participants remained comfortable and fully informed throughout their involvement.

Taken together, these chronological pre-engagement activities—objective alignment, purposive contact construction, automated and multi-channel outreach, logistical scheduling, instrument pre-testing, and staged consent—created a transparent, respectful, and efficient foundation for data collection. The approach both maximised participation opportunities across regions and improved the relevance and quality of the data feeding into the Talent Landscape Mapping & Pathways analysis for the GSMA African AI/LLM Language Models Initiative.

4.2.4 Secondary Data Sources

The report drew on multiple secondary data sources to complement survey and interview findings and provide a broader contextual understanding of Africa's AI/LLM talent landscape. The research compiled three complementary signal streams—research publications, job-market postings, and open-source repositories—using disciplined, API-driven collection pipelines and deterministic classification rules to ensure comparability across datasets.

For research publications, we harvested metadata from three platforms: Semantic Scholar, Scopus and Google Scholar via the Serper.dev endpoint. Each source was queried with cluster-aware search expressions (the project's seven AI skill clusters) combined with country and contextual keywords so that papers could be attributed to national ecosystems. Because affiliation filtering capabilities differed by source, the pipeline applied a two-stage geographic filter: (a) server-side AFFILCOUNTRY filtering where available (Scopus), and (b) local post-processing that matched author affiliations, institution and city names, and title/abstract terms to country keyword lists. All results were deduplicated by persistent identifiers (paperId/eid or normalized title), assigned to one of seven clusters by deterministic keyword matching in title+abstract, enriched with truncated abstracts, author/affiliation snippets, citation counts and the original query, and exported as country-level CSVs for analysis. The full secondary-data protocol and processing logic are described in the project's collection document.

A comprehensive AI **job market analysis** was conducted, focusing on AI/ML/LLM-related job postings across the continent. This analysis captured information on the number of AI job posting for each of the seven skill clusters, as well as distribution trends by country, region, job title, company, posting URL, posting date, relevant keywords, company AI/LLM job count. For **labour-market signals,** the team used three API sources to capture a snapshot of active demand during the research window. Aggregated job listings were collected through the JSearch provider on RapidAPI, South Africa-specific postings through the Adzuna API, and additional country-level coverage from the official LinkedIn Jobs API. Queries were constructed from the seven cluster keyword lists (for example, "LLM engineer", "data pipeline", "MLOps") and executed per ISO country code to generate country-tagged job signals. Each posting was captured with canonical fields (title, company, location, posting date, full description, application URL), normalized for location, deduplicated by job identifier or identical title+company within a short window, and classified into one or more skill clusters via deterministic keyword matching. The job dataset represents a time-bound snapshot (Q4-2025 to Q1-2026) and was explicitly treated as a demand indicator rather than a longitudinal labour-force census; methodological caveats (remote listings, informal work under-capture) were documented and mitigated through triangulation with the other signal streams.

Open-source capability was measured via systematic collection from the GitHub REST API using a three-phase discovery strategy. Phase one harvested repositories from a curated list of known African AI organisations. Phase two executed broad GitHub searches across topic, country+keyword, language+AI, city, university and dataset-oriented queries to maximize recall. Phase three ran country-specific queries for all 54 African countries. Country attribution was always PII-safe and based solely on repository metadata (name, description, topics): matches on city names, African language mentions, explicit country names, demonyms and references to known African initiatives (e.g., Masakhane) were used to map repos to countries; repositories without geographic signals were classified as 'Unclassified' and excluded. Each repository was classified into the seven clusters via keyword matching against name+description+topics, deduplicated by repo full name, enriched with stars/forks/language and timestamps, and output as an incremental CSV. Rate-limit handling, retry logic, and resumable progress tracking were embedded to preserve robustness and reproducibility. The GitHub pipeline's heuristics, limits and known blind spots (e.g., 1,000-result query cap, metadata-only country attribution) are documented in the collection protocol.

Across all three streams the team implemented consistent quality controls: deterministic de-duplication keyed on stable identifiers, rule-based cluster assignment to preserve interpretability, conservative geographic attribution designed to avoid false positives, logging for auditability, and export to standardized CSVs to support cross-pillar triangulation and analytics. Ethics and privacy safeguards were enforced throughout: no personal data beyond public contributor metadata was collected, scraping beyond authorised APIs was avoided, and results were reported only in aggregated form. The approach therefore delivers three harmonized, country-attributed datasets—publications, job postings, and repositories—that can be compared directly to surface alignment gaps while respecting provenance, reproducibility and data-use constraints.

4.3 Skill Clusters Used

The report adopted a structured framework comprising seven core skill clusters to assess the AI/LLM talent landscape across Africa. These clusters were identified based on consultations with experts, the GSMA Talent Workstream's objectives, and a review of relevant literature and industry practices. The clusters provided a standardised lens to evaluate both the availability and importance of skills in different regions, and to inform the design of actionable talent pathways.

The seven skill clusters were as follows:

1. **Foundational AI/LLM Engineering** – encompassing model architectures, fine-tuning techniques, inference optimisation, and core machine learning engineering skills required to build and adapt language models.
2. **Data Engineering for AI** – covering data pipelines, data cleaning and quality assurance, multilingual data handling, and the infrastructure necessary to prepare training data at scale.
3. **Linguistic & Cultural Expertise** – including translation, annotation, language proficiency, and cultural context knowledge essential for developing AI systems that function effectively in African languages and contexts.
4. **Evaluation & Quality Assurance** – focusing on benchmarking, testing methodologies, validation frameworks, bias detection, and systematic assessment of model performance and safety.
5. **Applied Product & Deployment** – integrating AI models into products, designing user experiences, and ensuring that AI solutions were delivered effectively to end users.
6. **Governance, Ethics & Safety** – covering responsible AI practices, policy frameworks, risk assessment, and compliance requirements to ensure ethical and safe AI development and deployment.

7. **MLOps/LLMOps** – encompassing the operational infrastructure to deploy, monitor, and maintain AI systems at scale, including model versioning, continuous integration, monitoring, and production reliability.

The adoption of these clusters allowed the report to systematically capture the state of AI/LLM skills across Africa, highlight regional strengths and weaknesses, and provide a structured foundation for subsequent gap analysis and pathway design.

4.4 Scoring Framework

The research adopted a structured scoring framework to quantify and prioritise skills across the seven identified clusters. For each skill, experts were asked to rate the following dimensions on a five-point scale (1–5):

- **Importance:** Respondents assessed the current significance of the skill for AI/LLM development in their region, with higher scores indicating greater relevance.
- **Availability:** Respondents evaluated the extent to which the skill was currently accessible within the region, with higher scores reflecting broader availability.
- **Geographic Spread:** Respondents indicated the distribution of the skill across countries, cities, and institutions within their operational regions, allowing for identification of concentrated hubs and regional disparities.
- **Confidence:** Respondents reported the level of certainty in their assessment of each skill, with higher scores indicating stronger confidence in the accuracy of their ratings.

These dimensions were designed to provide a multi-faceted understanding of the skills landscape, capturing both the demand for and the supply of expertise. The scoring framework facilitated the computation of priority scores, which were subsequently used to identify critical gaps and inform the design of talent pathways across Africa.

4.5 Priority Gap Formula

To identify and rank critical skill gaps across African AI/LLM talent clusters, this report adopted a quantitative prioritization approach based on expert assessments of **skill importance (demand)** and **skill availability (supply)**. This approach is grounded in established skills gap analysis and workforce planning methodologies, which consistently emphasize that priority gaps emerge where skills are highly important (high demand) but insufficiently available (low supply). Rather than treating importance and availability independently, the method integrates both dimensions into a single composite indicator that reflects the relative urgency (priority gap) of intervention for each skill cluster.

The priority score is calculated using the formula: **Priority = Importance × (6 − Availability)**. The logic underpinning this formulation aligns with widely used needs-assessment frameworks, which conceptualize skill gaps as a function of the difference between required competence (importance) and existing capacity (availability). In many applied studies, this relationship is expressed either as a gap matrix (high importance/low availability = critical gap) or as a numerical index that weights importance against scarcity. By multiplying importance with an inverted availability score **(6 − Availability)**, the formula ensures that skills that are both strategically vital and scarce receive the highest priority, while skills that are either less important or already abundant receive lower priority.

Note that the term **(6 − Availability)** is used to transform the original 1–5 availability scale into a **scarcity index**, where lower availability corresponds to higher scarcity. The governing assumption is that there is no AI/LLM talent cluster with 100% availability. The survey scale ranges from 1 (very low availability) to 5 (very high availability). Subtracting the availability score from 6 (i.e., one unit above the maximum scale value) inverts this scale while preserving its linear properties. This ensures that: (i) a skill rated 5 in availability (very high) yields a scarcity value of 1, minimizing its priority gap; (ii) a skill rated 1 in availability (very low) yields a scarcity value of 5, maximizing its contribution to the priority/urgency score; and (iii) the full 1–5 range is retained without introducing negative values or distortions. The use of 6, therefore, is not arbitrary but mathematically necessary to invert a 1–5 scale while maintaining proportional relationships across ratings.

This multiplicative structure also reflects the intuitive principle that **high importance alone does not create a priority gap if availability is also high**, and **low availability alone does not justify prioritization if importance is low**. For example, a skill rated very important (5) but highly available (5) yields a low priority score of $5 \times (6 - 5) = 5$, indicating that it is strategically significant but not an urgent gap. Conversely, a skill rated very important (5) but very scarce (1) yields a high priority score of $5 \times (6 - 1) = 25$, signaling a critical area for intervention. This approach therefore produces a balanced, interpretable ranking that is consistent with best practices in skills mapping and workforce planning.

Because both variables range from **1 to 5**, the **theoretical minimum and maximum** priority gap scores are:

Minimum possible score = 1

This occurs when: Importance = 1 (Very Low), Availability = 5 (Very High)

Calculation: 1 × (6 − 5) = **1**

Maximum possible score = 25

This occurs when: Importance = 5 (Very High), Availability = 1 (Very Low)

Calculation: 5 × (6 − 1) = **25**

Therefore, the priority gap score can range from: 1 to 25

Table 2: Full matrix of possible priority gap scores

Importance ↓ / Availability →	5 (Very High)	4	3	2	1 (Very Low)
5 (Very High)	5	10	15	20	**25**
4	4	8	12	16	20
3	3	6	9	12	15
2	2	4	6	8	10
1 (Very Low)	1	2	3	4	5

(Each cell = Importance × (6 − Availability))
20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low priority gap

4.6 Data Cleaning and Classification

To ensure analytical integrity and cross-dataset comparability, a structured data cleaning and classification framework was applied consistently across the three core data streams: AI job postings (9,937 records), AI research publications (25,489 records), and AI GitHub repositories (27,349 records). Given that the datasets were aggregated from multiple APIs and platforms, harmonization was essential to eliminate duplication, standardize taxonomies, and enable accurate regional and skill-based comparisons.

Deduplication was performed using deterministic rules tailored to each dataset. For research publications, persistent identifiers such as paper IDs and database-specific record numbers were used where available; in their absence, normalized title matching was applied to detect duplicate entries across sources. Job postings were deduplicated using job IDs, and where necessary, combinations of job title, company name, and posting date were used to remove repeated listings. GitHub repositories were deduplicated using unique repository full names and identifiers. This process ensured that each record represented a distinct unit of analysis, preventing inflation of counts and preserving the reliability of distributional statistics.

To enable cross-pillar alignment analysis, **standardized skill labels** were applied across all datasets using a unified seven-cluster AI skills framework: Foundational, Linguistic, Applied, Data Engineering, MLOps, Evaluation, and Governance. Classification was conducted through rule-based keyword matching within titles, abstracts, repository descriptions, and job descriptions. This deterministic approach ensured consistency across demand, research, and capability datasets, allowing for direct comparison of skill distribution patterns. Where multiple keywords were present, hierarchical logic was applied to assign the most appropriate primary cluster, reducing ambiguity and overlap.

Finally, **country and sector tagging** procedures were implemented to enable geographic and contextual analysis. Country attribution was derived from structured metadata fields where available (e.g., author affiliations, job locations, repository descriptors) and supplemented with validated keyword matching for institutions, cities, and national identifiers. Sector tagging for job postings was conducted using employer classification and contextual signals within job descriptions to distinguish industry domains where applicable. All geographic and sector assignments were reviewed through consistency checks to minimize misclassification and ensure robustness.

Together, these cleaning and classification procedures created a harmonized, high-integrity dataset that supports reliable cross-sectional and temporal comparisons across Africa's AI demand, knowledge production, and capability ecosystems.

4.7 Validation Process

To ensure the credibility, robustness, and policy relevance of the findings, a multi-layered validation process was implemented across all three data pillars—AI job demand (9,937 postings), AI research publications (25,489 records), and AI GitHub capability (27,349 repositories). Validation was designed not only to verify data accuracy but also to test the structural coherence of classifications, geographic attributions, and analytical outputs.

First, internal validation checks were conducted following data cleaning and classification. Frequency distributions were examined to detect anomalies, outliers, or implausible spikes across countries, regions, and skill clusters. Cross-tabulations were used to confirm that totals reconciled across aggregation levels, ensuring that country-level counts accurately summed to regional and continental totals. Random sampling of records within each dataset was undertaken to manually verify skill-cluster assignments and geographic tagging accuracy, particularly where keyword-based classification could introduce ambiguity.

Second, cross-source triangulation was applied as a structural validation mechanism. Patterns observed in job demand were compared with research output and GitHub activity to assess whether extreme deviations reflected genuine ecosystem differences or potential classification bias. For example, unusually high concentrations in specific clusters or countries were examined against alternative signals to confirm consistency. This triangulation reduced the risk of platform-specific distortions and strengthened confidence in comparative findings.

Third, stakeholder validation was incorporated through consultations with domain experts, workstream leads, and ecosystem practitioners. Preliminary findings were shared for feedback to assess face validity, contextual plausibility, and interpretive accuracy. This step was particularly important in validating regional specialization patterns and skill-cluster interpretations that may not be immediately evident from quantitative data alone.

Finally, methodological transparency was maintained throughout the process. All classification rules, deduplication logic, and country-tagging heuristics were documented, allowing reproducibility and external scrutiny. Where limitations were identified—such as potential underrepresentation of informal job markets or repositories lacking geographic signals—they were explicitly acknowledged to prevent over-interpretation.

Through this layered validation approach—statistical consistency checks, manual verification, cross-pillar triangulation, and expert review—the research ensured that its conclusions regarding Africa's AI demand, knowledge production, capability development, and alignment gaps are analytically sound and defensible.

4.8 Data Analysis

The report employed a multi-method data analysis approach to ensure rigour, triangulation, and policy-relevant insights from both quantitative and qualitative evidence.

Secondary quantitative data were analysed and visualised using **Microsoft Excel** and **Microsoft Power BI**, which enabled interactive and dynamic exploration of trends and patterns across regions and skill domains. Line graphs were used for trend analysis to track changes in AI/LLM skill demand and supply over time, providing a clear temporal perspective on emerging needs. Simple and component bar charts were applied to compare skill availability, importance, and regional distributions, while card visuals summarised key metrics such as total skills coverage and priority gap scores. Geospatial maps were utilised to visualise the geographic concentration of skills, allowing for intuitive interpretation of regional disparities and talent hubs. Power BI was selected for its scalability, interactivity, and capacity to integrate multiple data sources into a coherent analytical dashboard.

Descriptive statistical analysis was conducted using **SPSS** to provide a robust quantitative foundation for the skills mapping exercise. Frequency and percentage distributions were computed to summarise respondent characteristics and skill ratings across clusters. Measures of central tendency (mean) was used to assess overall patterns in skill importance and availability, as well as variability across regions. These statistics supported objective comparison across skill clusters and informed the calculation of priority gap scores.

An **AI Skills Priority Gap Score** was computed in SPSS using the formula:
Priority = Importance × (6 − Availability). This enabled the generation of a ranked skills list based on empirical evidence, ensuring that prioritisation was systematic, transparent, and replicable.

Qualitative interview data were analysed through **thematic analysis**, involving systematic coding, categorisation, and interpretation of expert responses. Emerging themes related to skills availability, barriers, pathways, and ecosystem dynamics were identified and used to contextualise and validate quantitative findings. This approach strengthened triangulation and ensured that numerical patterns were interpreted alongside practitioner perspectives.

All findings were synthesised, structured, and formatted in **Microsoft Word**, ensuring professional presentation, coherence, and alignment with GSMA reporting standards. The integration of statistical, visual, and thematic methods provided a comprehensive and credible analytical foundation for the report’s conclusions and recommendations.

CHAPTER 5: MAPPING AI TALENTS DEMAND IN AFRICA

This chapter analyses the structure and distribution of AI labour demand across Africa, based on a continental dataset of **9,937 AI job postings**. These postings represent the market-facing dimension of the AI ecosystem — where firms, governments, and institutions are actively seeking AI talent. As such, they provide the clearest indicator of economic absorption capacity and sectoral adoption.

The chapter examines how the 9,937 job postings are distributed across regions and countries, identifies which skill clusters dominate employer demand, and evaluates temporal trends to determine whether AI hiring is accelerating or stabilising. By grounding the analysis in the full continental demand total, this chapter establishes the economic baseline for the report. It answers the foundational question: **Where is AI talent economically demanded in Africa, and which skills dominate within the continent's 9,937 AI job opportunities?** Figure 2 presents an overview of AI Jobs demand across Africa.

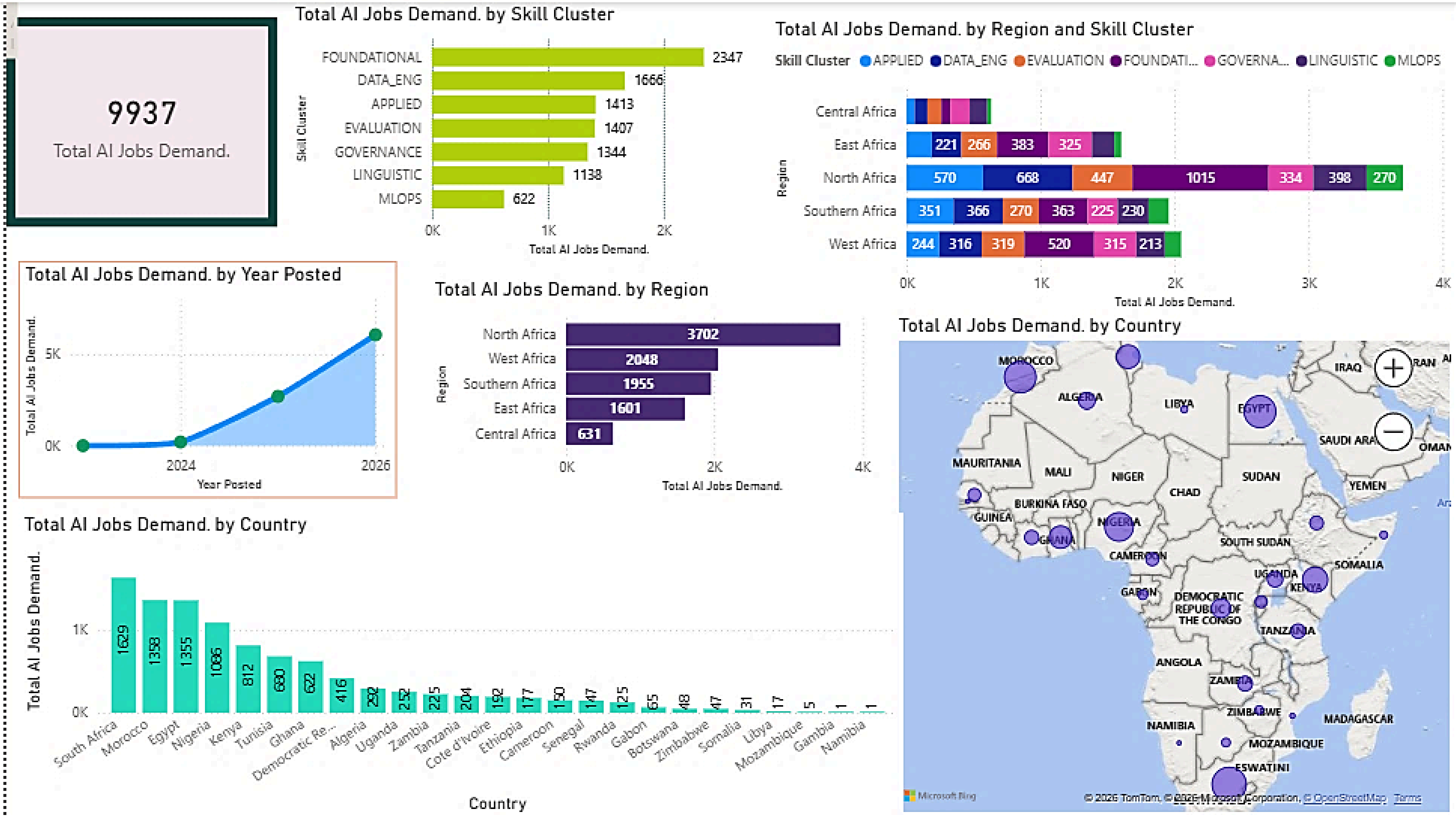


Figure 2: Overview of AI Jobs Demand Across Africa

5.1 Regional Distribution of AI-Related Job Demand in Africa

Across the full Africa-wide sample of 9,937 AI job postings, demand is clearly concentrated in a few sub-regions. Figure 3 reports the regional Distribution of AI-Related Job Demand in Africa

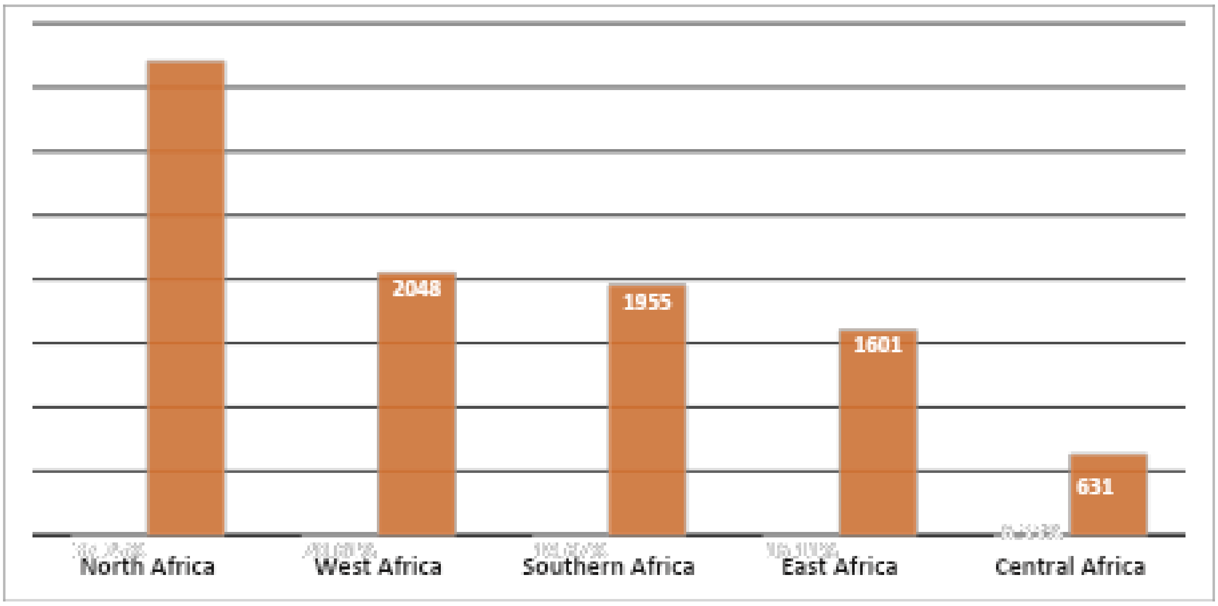


Figure 3: Regional Distribution of AI-Related Job Demand in Africa

North Africa accounts for the largest share at 37.25% of total postings, making it the dominant AI labour market on the continent. This is followed by West Africa (20.61%) and Southern Africa (19.67%), which contribute relatively comparable proportions. East Africa represents 16.11% of the continental total, while Central Africa remains significantly smaller at 6.35%. Thus, the African AI job market is structurally led by North Africa, with West and Southern Africa forming a second tier, and East and Central Africa contributing more modest shares.

5.2 Distribution of AI-Related Job Demand across Countries in Africa

The country-level distribution of AI job demand across Africa reveals a highly concentrated market structure, with a small number of countries accounting for the majority of postings. Figure 4 presents the distribution of AI-Related Job Demand across Countries in Africa.

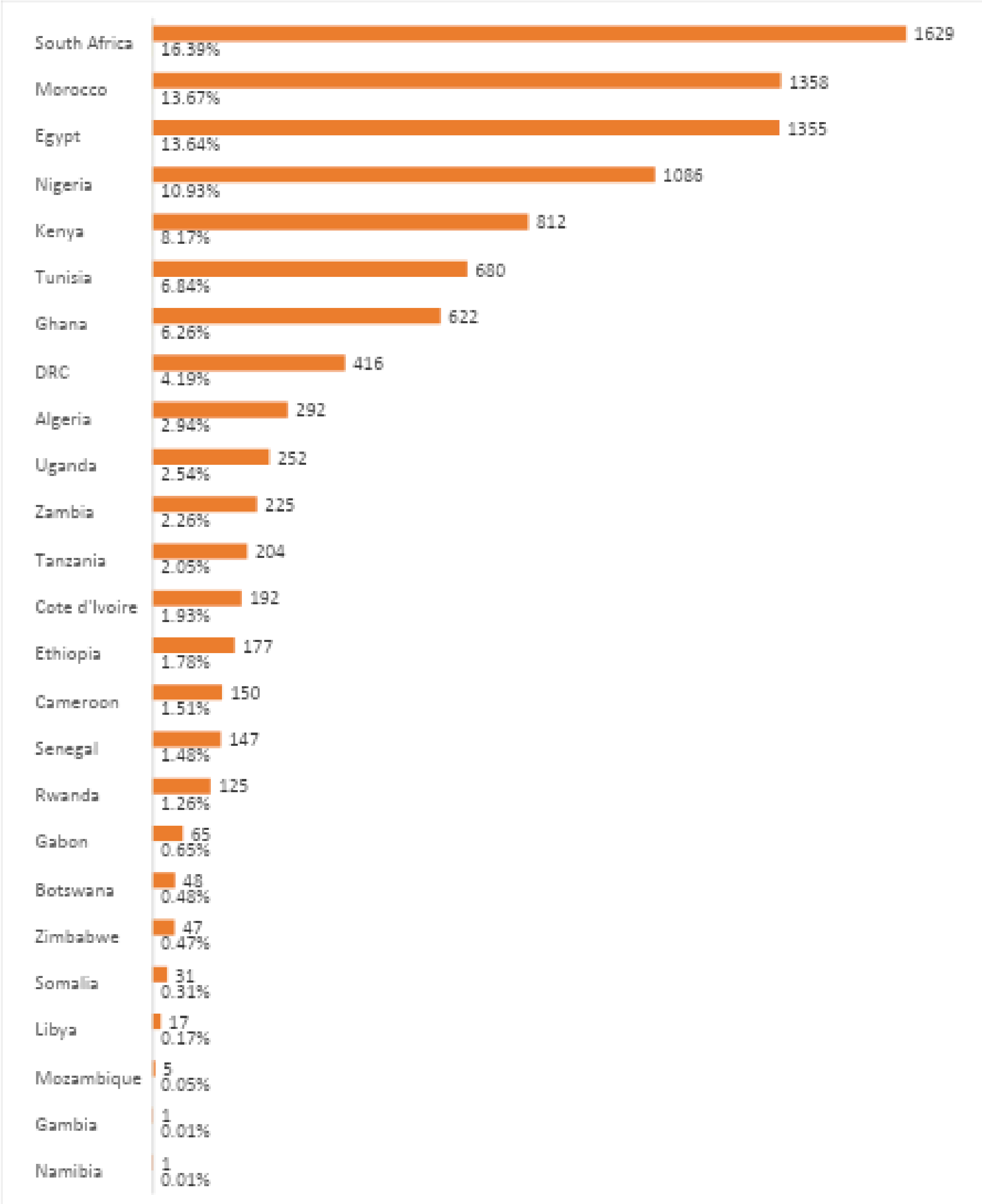


Figure 4: Distribution of AI-Related Job Demand across Countries in Africa

Out of the 9,937 total jobs identified, just five countries contribute nearly 63% of the continent's AI job demand, indicating that AI labour market activity is clustered in a limited set of national hubs.

South Africa emerges as the single largest AI job market, accounting for 16.39% of the total sample (1,629 jobs). It is followed closely by Morocco (13.67%) and Egypt (13.64%), both of which show nearly identical shares. Nigeria ranks fourth with 10.93%, while Kenya contributes 8.17%. Together, these five countries form the primary AI employment core of the continent, collectively shaping Africa's aggregate demand patterns.

A second tier of countries shows moderate but meaningful participation. Tunisia (6.84%) and Ghana (6.26%) demonstrate substantial AI labour market presence, though at roughly half the scale of the leading countries. Democratic Republic of the Congo accounts for 4.19%, while countries such as Algeria (2.94%), Uganda (2.54%), Zambia (2.26%), and Tanzania (2.05%) contribute smaller but still notable shares.

At the lower end of the distribution, several countries register minimal participation in the AI job market. These include Botswana, Zimbabwe, Gabon, Somalia, Libya, Mozambique, Namibia, and Gambia, each contributing less than 1% of total postings. While this does not necessarily indicate the absence of AI activity, it does suggest limited formalized job-market visibility within the dataset.

Several structural patterns emerge from this distribution. First, AI job demand in Africa is strongly concentrated in relatively diversified and economically larger markets. Second, North African countries—particularly Morocco and Egypt—feature prominently among the top performers, reinforcing earlier regional findings. Third, Sub-Saharan Africa's AI demand is largely anchored by South Africa, Nigeria, and Kenya, which together form the technological backbone of their respective sub-regions.

Overall, the country-level analysis confirms that Africa's AI job ecosystem is not evenly distributed but instead organized around a small number of dominant national hubs. These countries likely possess stronger digital infrastructure, more mature tech ecosystems, greater foreign investment presence, and more active private-sector demand for AI capabilities. This concentrated structure provides a critical foundation for subsequent country-specific and skill-cluster analyses.

5.3 Distribution of AI-Related Job Demand across Skill Clusters in Africa

The overall skill demand profile across Africa reveals a clear hierarchy of competencies that employers prioritize in AI-related job postings. Figure 5 shows the distribution of AI-Related Job Demand across Skill Clusters in Africa.

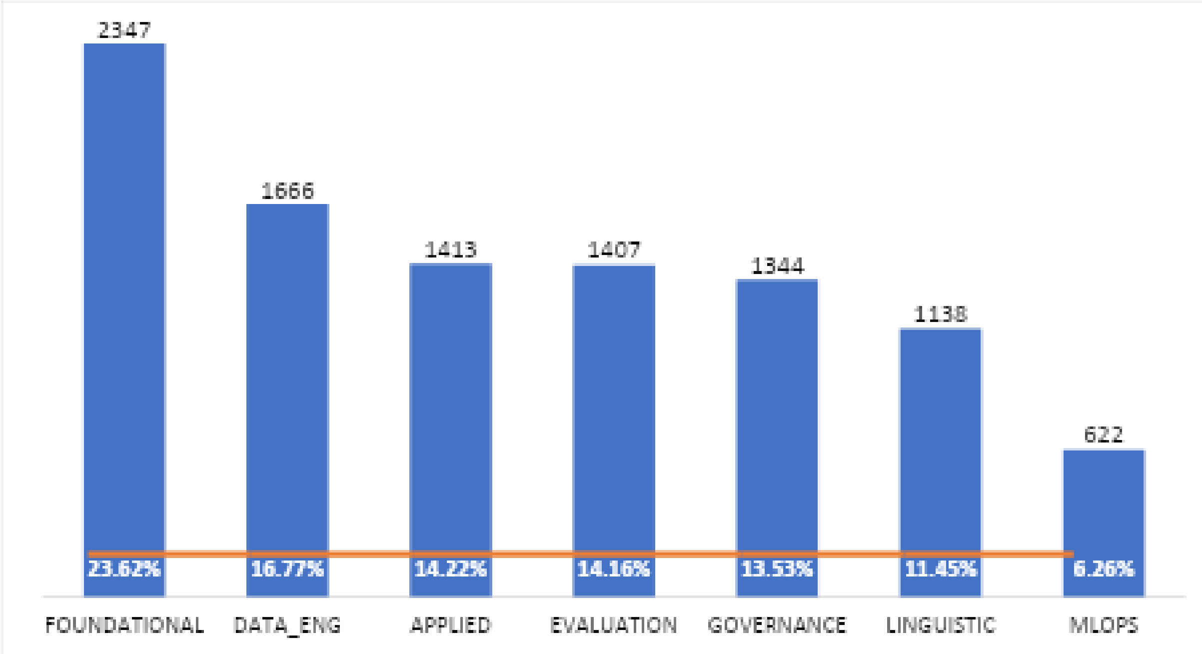


Figure 5: Distribution of AI-Related Job Demand across Skill Clusters in Africa

Out of a total of 9,937 roles, **Foundational AI skills** dominate the market with 2,347 jobs (23.62%), making it the most demanded cluster by a substantial margin. This indicates that employers place the highest value on core technical capabilities such as machine learning, algorithm development, mathematical modelling, and fundamental AI system design. The prominence of this cluster suggests that Africa's AI labour market is still strongly anchored in building and strengthening core technical capacity.

The second and third most demanded clusters are **Data Engineering** and **Applied AI**, with 1,666 jobs (16.77%) and 1,413 jobs (14.22%), respectively. Together, these categories account for a significant portion of total demand, reflecting the importance of data infrastructure, pipeline development, model implementation, and real-world deployment. The high demand for Data Engineering particularly highlights the central role of data collection, processing, storage, and management in enabling AI systems to function effectively. Employers are not only seeking model developers but also professionals capable of preparing and structuring the data required to power those models.

Evaluation skills represent 1,407 roles (14.16%), closely aligned with Applied AI in magnitude. This suggests that organizations are increasingly emphasizing model testing, validation, performance monitoring, and quality assurance. The relatively strong presence of Evaluation roles indicates growing awareness of the need for responsible development practices and performance accountability in AI systems.

Governance accounts for 1,344 jobs (13.53%), signalling significant demand for regulatory compliance, ethical oversight, risk management, and policy-aligned AI deployment. This substantial share reflects the increasing institutionalization of AI governance frameworks across organizations and countries, as employers recognize the importance of responsible AI practices.

Linguistic AI roles represent 1,138 jobs (11.45%). While smaller than the top clusters, this still constitutes a meaningful share of the market, suggesting continued demand for natural language processing, multilingual systems, and language-driven applications—particularly relevant in a linguistically diverse continent.

Finally, **MLOps** is the smallest cluster with 622 jobs (6.26%). Although comparatively limited, this category remains strategically important, as it relates to deploying, monitoring, and scaling AI models in production environments. Its lower share may indicate that while foundational development is expanding, large-scale operationalization of AI systems is still emerging in many parts of the continent.

Overall, the skill demand structure demonstrates that employers across Africa are primarily seeking core technical and infrastructure capabilities, followed by application, evaluation, and governance competencies. The dominance of Foundational and Data Engineering skills suggests that the continent's AI ecosystem is still in a capacity-building phase, emphasizing model development and data readiness, while deployment-oriented roles such as MLOps remain comparatively less widespread. This distribution provides a clear picture of the current priorities shaping Africa's AI labour market.

5.4 Sub-regional distribution of AI-Related Job postings by skills across Africa

The sub-regional distribution of AI skills across Africa shows clear dominance patterns within each skill cluster, reinforcing the earlier finding that North Africa leads overall demand while West and Southern Africa remain strong secondary hubs. Figure 6 shows the sub-regional distribution of AI-Related Job postings by skills across Africa

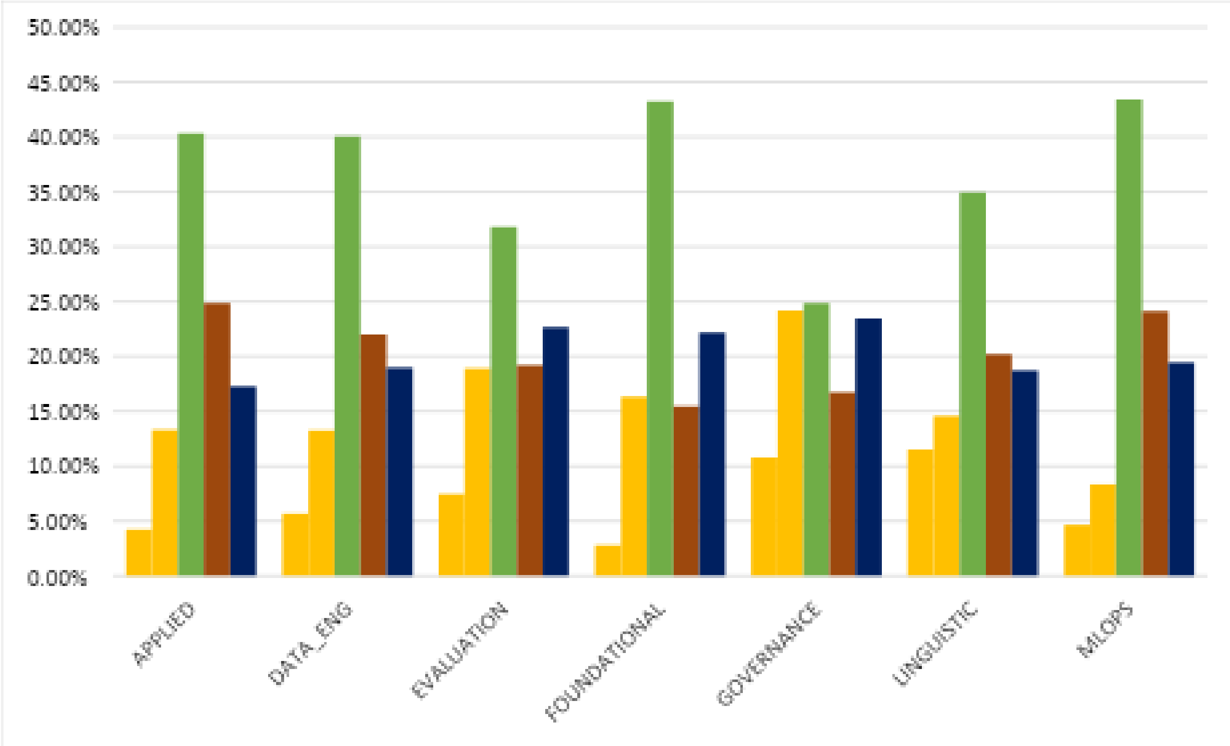


Figure 6: Sub-regional distribution of AI-Related Job postings by skills across Africa

In **Applied AI** (N = 1,413), North Africa dominates with 570 jobs (40.34%), followed by South Africa's broader sub-region, Southern Africa, with 351 jobs (24.84%). West Africa contributes 244 (17.27%), while East Africa accounts for 188 (13.31%), and Central Africa remains limited at 60 (4.25%). This indicates that applied AI roles are primarily concentrated in North Africa.

In **Data Engineering** (N = 1,666), North Africa again leads with 668 roles (40.10%). Southern Africa follows with 366 (21.97%), West Africa with 316 (18.97%), East Africa with 221 (13.27%), and Central Africa with 95 (5.70%). The dominance of North Africa in this infrastructure-oriented cluster highlights its strong technical foundation.

For **Evaluation** roles (N = 1,407), North Africa remains the largest contributor with 447 jobs (31.77%). West Africa shows strong representation with 319 (22.67%), followed by East Africa with 266 (18.91%) and Southern Africa with 270 (19.19%). Central Africa contributes 105 (7.46%). Unlike some other clusters, Evaluation demand is more evenly distributed, though North Africa still leads.

In the **Foundational** cluster (N = 2,347), North Africa is even more dominant, accounting for 1,015 jobs (43.25%). West Africa contributes 520 (22.16%), East Africa 383 (16.32%), Southern Africa 363 (15.47%), and Central Africa 66 (2.81%). This confirms that core AI development activity is heavily concentrated in North Africa.

Within **Governance** (N = 1,344), the distribution is comparatively balanced. North Africa leads slightly with 334 roles (24.85%), closely followed by West Africa with 315 (23.44%) and East Africa with 325 (24.18%). Southern Africa contributes 225 (16.74%), and Central Africa 145 (10.79%). Governance roles therefore appear more geographically dispersed than technical clusters.

In the **Linguistic** cluster (N = 1,138), North Africa again dominates with 398 jobs (34.97%). West Africa follows with 213 (18.72%), Southern Africa with 230 (20.21%), East Africa with 166 (14.59%), and Central Africa with 131 (11.51%). This reflects strong language-related AI activity in North Africa, with meaningful participation across other sub-regions.

Finally, in **MLOps** (N = 622), North Africa is the clear leader with 270 roles (43.41%), followed by Southern Africa with 150 (24.12%) and West Africa with 121 (19.45%). East Africa accounts for 52 (8.36%), and Central Africa for 29 (4.66%). This indicates that production-level AI deployment is highly concentrated, particularly in North Africa.

Overall, North Africa dominates every major skill cluster—especially Foundational, Data Engineering, MLOps, Applied, and Linguistic roles—confirming its leadership across both volume and technical depth. West and Southern Africa consistently rank as secondary hubs, particularly in Governance and Evaluation. East Africa maintains moderate participation across clusters, while Central Africa remains the least represented sub-region in all skill categories. This pattern demonstrates that Africa's AI skill demand is both geographically concentrated and functionally structured, with North Africa serving as the primary continental driver of AI specialization.

5.5 Country-Wide distribution of AI-Related Job postings by skills across Africa

The skill-cluster distribution by country reveals that dominance varies significantly depending on the segment of the AI value chain considered. While a few countries lead overall demand, leadership within specific technical clusters is more differentiated. Figure 7 presents the country-Wide distribution of AI-Related Job postings by skills across Africa

Country	APPLIED	DATA_ENG	EVALUATION	FOUNDATIONAL	GOVERNANCE	LINGUISTIC	MLOPS
Algeria	2.05%	3.60%	2.84%	3.11%	3.94%	3.16%	0.16%
Botswana	0.14%	0.72%	0.28%	0.26%	1.49%	0.35%	
Cameroon	0.71%	1.32%	1.63%	0.89%	3.35%	2.20%	0.64%
Cote d'Ivoire	0.78%	1.44%	3.13%	1.15%	4.02%	2.11%	1.29%
Democratic Republic of the Congo	3.11%	3.60%	5.26%	1.62%	6.70%	8.17%	2.73%
Egypt	14.30%	14.53%	12.72%	11.80%	9.08%	17.22%	22.03%
Ethiopia	1.49%	1.98%	2.77%	0.77%	3.20%	1.85%	0.32%
Gabon	0.42%	0.78%	0.57%	0.30%	0.74%	1.14%	1.29%
Gambia				0.04%			
Ghana	5.73%	7.02%	8.17%	4.60%	7.37%	6.33%	4.82%
Kenya	6.79%	6.84%	7.39%	10.40%	9.52%	7.56%	6.43%
Libya	0.42%			0.47%			
Morocco	15.00%	13.39%	9.95%	19.64%	6.99%	12.30%	14.15%
Mozambique	0.14%			0.13%			
Namibia	0.07%						
Nigeria	10.12%	8.70%	10.52%	15.25%	9.23%	8.61%	11.25%
Rwanda	0.99%	1.02%	1.63%	1.19%	2.75%	0.44%	0.16%
Senegal	0.64%	1.80%	0.85%	1.11%	2.83%	1.67%	2.09%
Somalia	1.06%	0.18%		0.43%		0.26%	
South Africa	21.87%	19.21%	13.36%	13.72%	9.75%	18.45%	23.95%
Tanzania	1.34%	1.32%	3.55%	1.32%	4.91%	1.32%	0.16%
Tunisia	8.56%	8.58%	6.25%	8.22%	4.84%	2.28%	7.07%
Uganda	1.63%	1.92%	3.55%	2.22%	3.79%	3.16%	1.29%
Zambia	2.26%	1.50%	4.98%	1.02%	4.39%	1.23%	0.16%
Zimbabwe	0.35%	0.54%	0.57%	0.34%	1.12%	0.18%	
Grand Total (%)	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Grand Total (N)	**1413**	**1666**	**1407**	**2347**	**1344**	**1138**	**622**

Figure 7: Country-Wide distribution of AI-Related Job postings by skills across Africa

In **Applied AI** (N = 1,413), South Africa leads decisively with 309 jobs (21.87%), followed by Morocco with 212 (15.00%), Egypt with 202 (14.30%), and Nigeria with 143 (10.12%). Kenya also maintains a strong presence with 96 roles (6.79%). This suggests that application-oriented AI roles are concentrated in the continent's most industrially and digitally advanced economies.

For **Data Engineering** (N = 1,666), South Africa again ranks first with 320 roles (19.21%), followed by Egypt with 242 (14.53%) and Morocco with 223 (13.39%). Nigeria contributes 145 roles (8.70%), while Kenya accounts for 114 (6.84%). These figures confirm that data infrastructure capabilities are most developed in the continent's largest AI markets.

In **Evaluation** roles (N = 1,407), South Africa leads with 188 jobs (13.36%), closely followed by Egypt with 179 (12.72%) and Nigeria with 148 (10.52%). Morocco contributes 140 roles (9.95%), and Ghana stands out with 115 (8.17%). This indicates a relatively more distributed structure compared to Applied and Data Engineering clusters.

The **Foundational AI** cluster (N = 2,347), the largest overall, is dominated by Morocco with 461 roles (19.64%), followed by Nigeria with 358 (15.25%), South Africa with 322 (13.72%), Egypt with 277 (11.80%), and Kenya with 244 (10.40%). This confirms Morocco's particularly strong specialization in core AI model development, positioning it as the continent's leading hub for foundational AI expertise.

In **Governance** (N = 1,344), Nigeria records 124 roles (9.23%), closely aligned with South Africa's 131 (9.75%) and Egypt's 122 (9.08%). However, the **Democratic Republic of the Congo** shows a notable 90 roles (6.70%), and Ghana contributes 99 (7.37%). Governance demand is therefore more evenly spread across several countries rather than concentrated in a single dominant hub.

The **Linguistic AI** cluster (N = 1,138) is led by South Africa with 210 jobs (18.45%) and Egypt with 196 (17.22%). Morocco follows with 140 (12.30%), while Nigeria and Kenya contribute 98 (8.61%) and 86 (7.56%), respectively. The Democratic Republic of the Congo also stands out with 93 roles (8.17%), reflecting strong participation in language-related AI tasks.

Finally, in **MLOps** (N = 622), South Africa dominates with 149 roles (23.95%), followed by Egypt with 137 (22.03%) and Morocco with 88 (14.15%). Nigeria contributes 70 roles (11.25%), while Kenya and Tunisia account for 40 (6.43%) and 44 (7.07%), respectively. This indicates that production-level AI deployment and operational scaling remain highly concentrated in a few technologically mature markets.

Overall, three structural insights emerge. First, South Africa consistently ranks either first or second across nearly all clusters, particularly in Applied, Data Engineering, Linguistic, and MLOps roles. Second, Morocco dominates Foundational AI, reinforcing its technical depth in core model development. Third, Egypt maintains strong cross-cluster representation, especially in Data Engineering and MLOps.

Nigeria and Kenya also maintain significant multi-cluster influence but do not dominate any single category outright. This cluster-level breakdown shows that while overall AI demand is concentrated in a handful of countries, specialization patterns vary, reflecting differentiated ecosystem strengths across the continent.

5.6 Overall AI labour market structure across Africa

The overall AI labour market structure across Africa indicates that demand is **concentrated rather than broadly distributed**, although the degree of concentration varies depending on whether the analysis is conducted at the regional, country, or skill level. When synthesizing regional, country, and skill dimensions together, the evidence consistently points toward structural clustering around a limited number of hubs.

5.6.1. Regional concentration

From a **regional perspective**, demand is heavily concentrated in North Africa, which accounts for 37.25% of total jobs. It is followed by West Africa (20.61%) and Southern Africa (19.67%). In contrast, East Africa (16.11%) and Central Africa (6.35%) contribute substantially smaller shares. This uneven distribution demonstrates clear regional clustering, with one dominant hub and two secondary centers.

5.6.2. Country concentration

At the **country level**, concentration is even more pronounced. Just five countries—South Africa (16.39%), Morocco (13.67%), Egypt (13.64%), Nigeria (10.93%), and Kenya (8.17%)—collectively account for nearly two-thirds of total AI job postings. The remaining countries each contribute relatively small proportions. This indicates strong national-level clustering, where AI demand is concentrated in a limited number of digitally advanced economies.

5.6.3. Skill concentration

In terms of **skill concentration**, demand is moderately concentrated in foundational competencies. **Foundational AI** alone represents 23.62% of total demand, making it the single largest cluster. When combined with **Data Engineering** (16.77%) and **Applied AI**

(14.22%), these three technical categories account for more than half of all roles. This suggests that employers prioritize core development and infrastructure capabilities. However, the presence of meaningful shares in **Evaluation** (14.16%), **Governance** (13.53%), and **Linguistic** skills (11.45%) indicates that the market is not narrowly specialized in only one function. **MLOps**, while smaller at 6.26%, further reflects emerging operationalization demand.

5.6.4. Time concentration (growth trend)

The **time dimension** of the AI labour market across Africa indicates a strong and accelerating growth trajectory, suggesting increasing demand intensity rather than stagnation.

Annual Distribution of Africa's AI Jobs Demand across Skill Cluster

Figure 8 shows the annual distribution of Africa's AI Jobs Demand across Skill Cluster

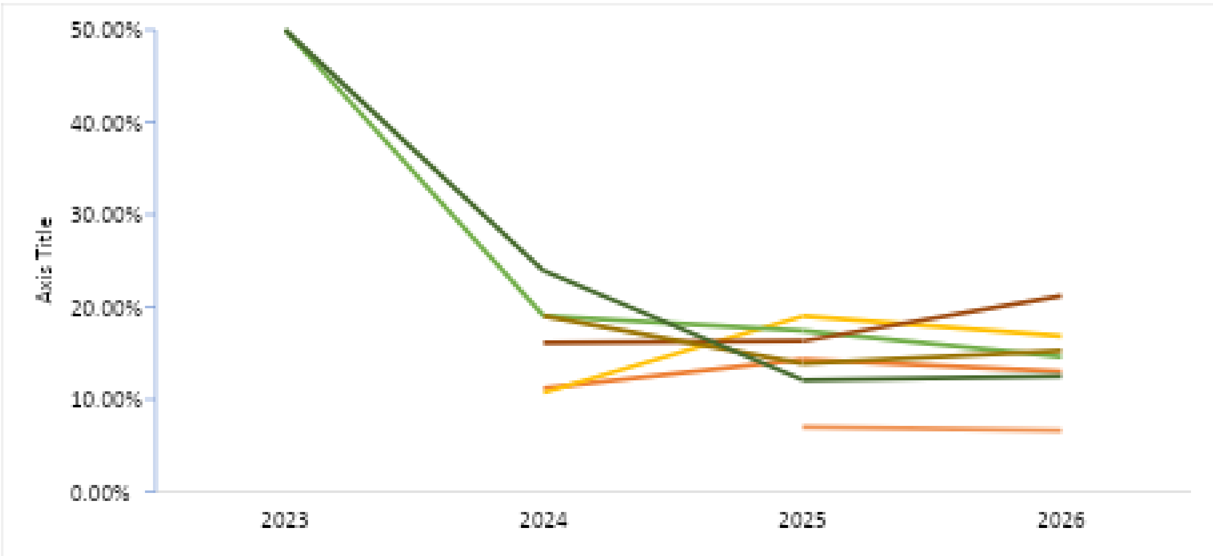


Figure 8: Annual Distribution of Africa's AI Jobs Demand across Skill Cluster

Job postings rise sharply over time, with minimal activity in 2023 (only 2 roles), moderate expansion in 2024 (205 roles), substantial growth in 2025 (2,686 roles), and a dramatic surge in 2026 (6,065 roles). This pattern clearly demonstrates strong temporal concentration in the most recent years, particularly 2025–2026.

The data show that **over 94% of total observed jobs are concentrated in 2025 and 2026**, indicating that AI demand is highly recent and rapidly expanding. The exponential increase between 2024 and 2026 reflects accelerating market adoption, organizational digital transformation, and growing institutional investment in AI capabilities. This trend suggests that Africa's AI labour market is still in a growth phase rather than a mature or saturated stage.

When examining **skill distribution over time**, growth is broad-based but uneven across clusters. In 2026—the peak year—Foundational roles dominate with 1,284 jobs (21.17% of that year's total), followed by Data Engineering (1,020; 16.82%) and Governance (927; 15.28%). Applied AI (789; 13.01%), Evaluation (885; 14.59%), and Linguistic roles (758; 12.50%) also show substantial expansion. MLOps accounts for 402 roles (6.63%), reflecting growing but still comparatively smaller operationalization demand.

In 2025, Data Engineering (510; 18.99%) and Evaluation (468; 17.42%) were particularly strong, while Governance (372; 13.85%) and Applied AI (385; 14.33%) also recorded significant growth. This suggests that earlier expansion phases focused heavily on infrastructure and validation capabilities before shifting further toward foundational scaling in 2026.

The temporal pattern therefore indicates **rapid market acceleration rather than long-term stagnation**, but also reveals that growth is concentrated in the most recent period. The near absence of activity before 2024 implies that the AI labour market in Africa is a relatively new and rapidly developing phenomenon within the dataset. Moreover, the surge in Foundational and Data Engineering roles in 2026 reinforces the structural emphasis on core technical capacity as demand expands.

Annual Distribution of Africa's AI Jobs Demand across each Region

The data clearly show **strong time concentration by region**, and the growth pattern differs meaningfully across sub-regions within Africa. Overall, AI job demand is not only accelerating over time, but the acceleration is **regionally uneven**, with some regions experiencing much sharper late-stage growth. Figure 9 reports the annual distribution of Africa's AI Jobs Demand across each Region

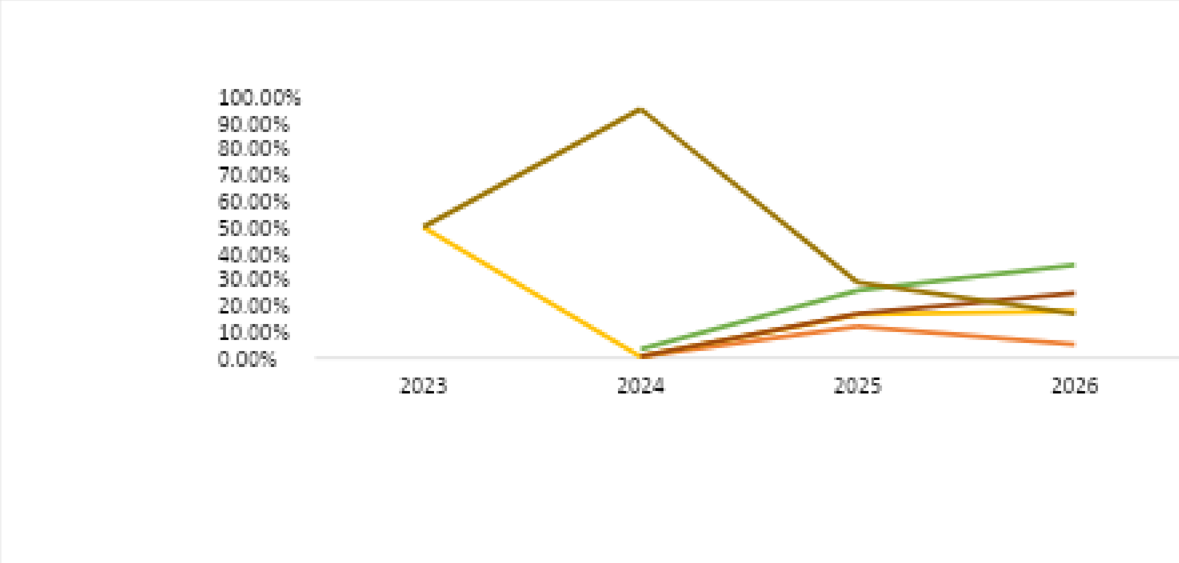


Figure 9: Annual Distribution of Africa's AI Jobs Demand across each Region

First, the most significant temporal shift occurs in **North Africa**. North Africa accounts for only 3.41% of regional jobs in 2024, rises to 25.73% in 2025, and then surges to **35.52% in 2026**. This indicates extremely strong recent acceleration, making North Africa the dominant growth engine in the latest year. The sharp increase between 2025 and 2026 demonstrates that demand is highly time-concentrated in the most recent period.

Second, **Southern Africa** shows a similar acceleration pattern. Its share rises from 0.49% in 2024 to 16.83% in 2025 and then increases substantially to **24.67% in 2026**. This indicates strong late-stage expansion, particularly in the most recent year, reinforcing its position as a major secondary growth hub.

Third, **East Africa** demonstrates steady but pronounced growth. After minimal activity in 2024 (0.49%), it grows to 16.64% in 2025 and slightly increases to **17.94% in 2026**. While not as explosive as North Africa, East Africa shows consistent upward momentum, indicating sustained expansion rather than short-term spikes.

Fourth, **West Africa** presents a different trajectory. It dominates early growth in 2024 (95.12% of that year's total), rises to 28.74% in 2025, but declines to 16.83% in 2026. This suggests that West Africa experienced earlier concentration of demand, followed by relative share reduction as other regions accelerated more rapidly in 2026. Its growth appears earlier but less dominant in the latest phase.

Finally, **Central Africa** remains the least concentrated region over time. Although it increases in absolute numbers between 2024 and 2025, its share declines significantly in 2026 (from 12.06% in 2025 to 5.05% in 2026). This suggests that while growth exists, it is comparatively slower relative to other regions.

Annual Distribution of Africa's AI Jobs Demand across each Country

The data clearly demonstrate **strong time concentration by country**, with substantial acceleration in 2025 and especially 2026 across the dominant AI markets in Africa. The pattern shows that AI job demand is not evenly distributed over time; instead, it is heavily clustered in the most recent years, and the growth dynamics vary significantly across countries. Figure 10 shows the annual distribution of Africa's AI Jobs Demand across each Country.

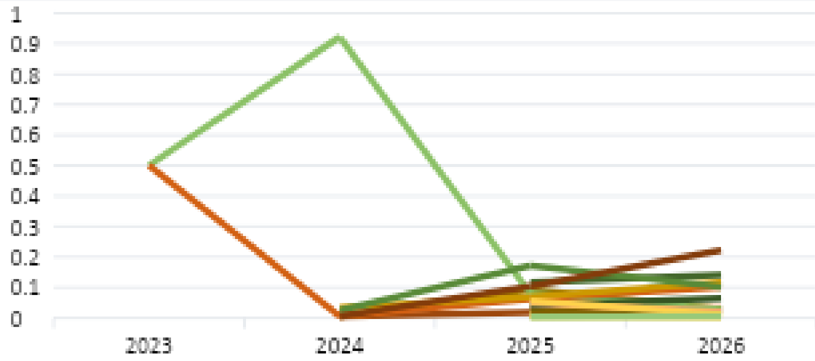


Figure 10: Annual Distribution of Africa's AI Jobs Demand across each Country

First, the most pronounced recent acceleration occurs in **South Africa**. Its share rises sharply from 0.49% in 2024 to 10.39% in 2025, and then surges to **22.24% in 2026**. This indicates very strong late-stage growth, making South Africa the dominant contributor to the most recent expansion phase.

Similarly, **Egypt** shows substantial time concentration. While it had no meaningful presence in earlier years, it accounts for 11.65% in 2025 and increases further to **14.23% in 2026**. This steady upward trajectory reflects sustained and accelerating demand.

Morocco also demonstrates clear growth momentum, rising from 3.41% in 2024 to 7.00% in 2025 and reaching **11.66% in 2026**. This pattern suggests expanding AI ecosystem maturity with strong recent scaling.

In **Nigeria**, demand peaks in 2025 (17.16%) but slightly declines to 10.11% in 2026. This indicates earlier concentration of growth followed by relative share adjustment as other countries accelerated more strongly in 2026.

Kenya shows consistent expansion over time, increasing from 6.18% in 2025 to **10.22% in 2026**, reflecting steady growth rather than volatility.

Some countries show earlier spikes. For example, **Ghana** records extremely high concentration in 2023–2024 (50% and 92.20%), but its share declines sharply in 2025 and 2026. This suggests early-period dominance in the dataset, followed by relative reduction as the continental market expanded and diversified.

Other countries such as **Democratic Republic of the Congo** show a sharp rise in 2025 (9.27%) but lower share in 2026 (2.74%), indicating short-term concentration rather than sustained long-term growth.

5.7 AI/LLM Talent Demand by Sector

Table 3 shows the distribution of AI/LLM Talent Demand by Sector The survey responses indicate that startups are the most dominant source of demand for AI and LLM talent across the African ecosystem.

Table 3: Frequency and Percentage Distribution of AI/LLM Talent Demand by Sector

Sector	Frequency	Percentage (%)
Startups	11	21.6%
Financial Services	9	17.6%
Telcos	8	15.7%
International Companies	6	11.8%
Government	5	9.8%
Academia / Research	4	7.8%
NGOs / Development Sector	2	3.9%
Healthcare	1	2.0%

All eleven respondents identified startups as active employers of AI talent, representing **21.6% of all sector mentions** in the survey. This strong representation suggests that early-stage and innovation-driven companies are currently the primary drivers of AI job creation across the continent. The prominence of startups reflects the rapid expansion of AI-enabled digital solutions in areas such as fintech, mobility, health technology, and enterprise services, where smaller and more agile firms are often quicker to adopt and deploy emerging technologies.

The **financial services sector** emerges as the second most significant source of AI talent demand. It appears in **9 out of the 11 responses**, accounting for **17.6% of total sector mentions**. This strong presence highlights the central role of banks, fintech companies, and digital payment providers in adopting AI technologies for fraud detection, risk modelling, customer analytics, and automated financial services. Closely following financial services is the **telecommunications sector**, which represents **15.7% of all sector mentions**. Telecommunications companies across Africa increasingly integrate AI into network optimisation, customer service automation, predictive maintenance, and data-driven service delivery, which explains their strong demand for AI professionals.

The survey also indicates a significant contribution from **international companies**, which represents **11.8% of all sector mentions**. These organisations—often multinational technology firms, consulting companies, or globally distributed development teams—play an important role in absorbing African AI talent, frequently through remote work arrangements or regional innovation hubs. Their presence suggests that Africa's AI workforce is increasingly integrated into the global digital economy.

Government institutions accounts for **9.8% of total sector mentions**. This indicates a growing but still moderate role of the public sector in AI employment. Governments across the continent are gradually adopting AI for digital governance, data-driven policy analysis, and smart public services, though their demand remains lower than that of the private sector. Similarly, **academia and research institutions** represent **7.8% of sector mentions**. These institutions play an important role in training AI talent and conducting research, but their capacity to absorb large numbers of AI professionals remains more limited compared to industry employers.

Two sectors appear more constrained in their current demand for AI talent. The **NGO and development sector** was mentioned in **2 responses**, representing **3.9% of sector mentions**. While development organisations increasingly use AI for social impact initiatives such as data analysis, humanitarian logistics, and public health modelling, their overall demand for specialised AI professionals remains relatively small. Finally, **healthcare** was identified in only **one response**, accounting for **2.0% of sector mentions**. This suggests that AI adoption in the health sector is still emerging across many African countries, likely constrained by regulatory frameworks, infrastructure limitations, and limited digitisation of health records.

Overall, the findings indicate that **Africa's AI talent demand is strongly concentrated in the private sector**, particularly among startups, financial services firms, and telecommunications companies. Public sector institutions, academia, and development organisations play supporting roles, while healthcare remains an emerging domain. This sectoral distribution reflects the broader structure of the continent's digital economy, where innovation-driven startups and fintech ecosystems are currently the most active adopters of artificial intelligence technologies.

5.8 Summary

The evidence in this chapter suggests that Africa's AI labour market is **structurally concentrated geographically**, particularly at the country level, but **moderately diversified in skill composition**. Demand is not evenly spread across regions or countries; instead, it is anchored in a small number of dominant hubs, especially in North and Southern Africa. At the same time, within these hubs, employers seek a broad mix of technical, applied, governance, and language-related competencies. Therefore, the market can best be described as **geographically concentrated but functionally diversified**, rather than fully broad-based.

In addition, the time-based analysis shows that AI demand in Africa is **strongly growth-concentrated in the most recent years**, particularly 2025 and 2026, with expansion occurring across all skill clusters. This confirms that the market is not only geographically concentrated but also temporally accelerating, reflecting a dynamic and rapidly evolving AI ecosystem rather than a stable or mature one.

Furthermore, there is clear **time concentration of AI job demand across regions**, particularly in 2025–2026. However, the growth is unevenly distributed. North Africa and Southern Africa show the strongest recent acceleration, East Africa demonstrates steady expansion, West Africa experienced earlier concentration but relative decline in the latest surge, and Central Africa remains comparatively limited. Therefore, AI demand in Africa is not only geographically concentrated but also temporally accelerating in specific high-growth regions, especially in the most recent year.

The temporal pattern further shows that AI job demand across Africa is **highly time-concentrated in 2025–2026**, with the strongest recent growth occurring in South Africa, Egypt, and Morocco. Nigeria and Kenya also show meaningful expansion, though with slightly different trajectories. Earlier years (2023–2024) account for a very small fraction of total demand, confirming that Africa's AI labour market is a **rapidly accelerating and recently intensified phenomenon**, rather than a long-established, evenly distributed trend. Therefore, there is clear **country-level time concentration**, with most major markets experiencing significant growth in the most recent period — especially 2026 — reinforcing the conclusion that Africa's AI demand is both structurally concentrated and dynamically expanding. Table 4 summarises the overall synthesis of Africa AI Job demand

Table 4: Overall Synthesis of Africa AI Job demand

Question	Evidence-Based Answer (with Data)
Where is hiring happening?	● Regionally led by **North Africa (37.25%)**, followed by **West Africa (20.61%)** and **Southern Africa (19.67%)**. ● Country-level leaders are **South Africa (16.39%)**, **Morocco (13.67%)**, **Egypt (13.64%)**, **Nigeria (10.93%)**, and **Kenya (8.17%)**, these countries jointly account for ≈63% of total demand.
Who dominates?	● **Regional dominance:** North Africa (37.25%). ● **Country dominance:** South Africa (16.39%). ● **Skill dominance: Foundational AI** (2,347 jobs; 23.62%), followed by **Data Engineering** (1,666; 16.77%) and **Applied AI** (1,413; 14.22%). ● In 2026, North Africa accounts for **35.52%** of regional demand.
What skills are in demand?	● Highest demand is for **Foundational (23.62%)**, **Data Engineering (16.77%)**, **Applied (14.22%)**, **Evaluation (14.16%)**, and **Governance (13.53%)**. **Linguistic** = 11.45%. **MLOps** = 6.26%.

Concentrated or broad?	● **Geographically concentrated** (top 5 countries ≈63% of demand; North Africa alone 37.25%). ● **Skill structure is diversified**, with demand spread across technical, governance, evaluation, and operational clusters. ● **Time is highly concentrated in 2025–2026**, which account for the vast majority of the AI jobs postings in Africa. ● Overall: *concentrated in location and time, moderately broad in skills.*

CHAPTER 6: MAPPING AI KNOWLEDGE PRODUCTION IN AFRICA

This chapter examines Africa's AI research landscape, drawing on a comprehensive dataset of 25,489 AI research publications across the continent. Research output reflects intellectual capacity, scientific infrastructure, and long-term innovation potential. Unlike job postings, which signal immediate market needs, publications represent foundational knowledge creation. The analysis maps the regional and country-level distribution of the 25,489 publications, evaluates concentration patterns, identifies dominant research skill clusters, and assesses temporal growth trends.

Particular attention is given to whether research activity is broad-based or concentrated among a few leading countries. By analysing the continent's 25,489 publications, this chapter answers the question: Where is AI knowledge produced in Africa, and what structural patterns define its academic ecosystem? Figure 11offers a general overview of AI Knowledge Production (Research Publications) in Africa.

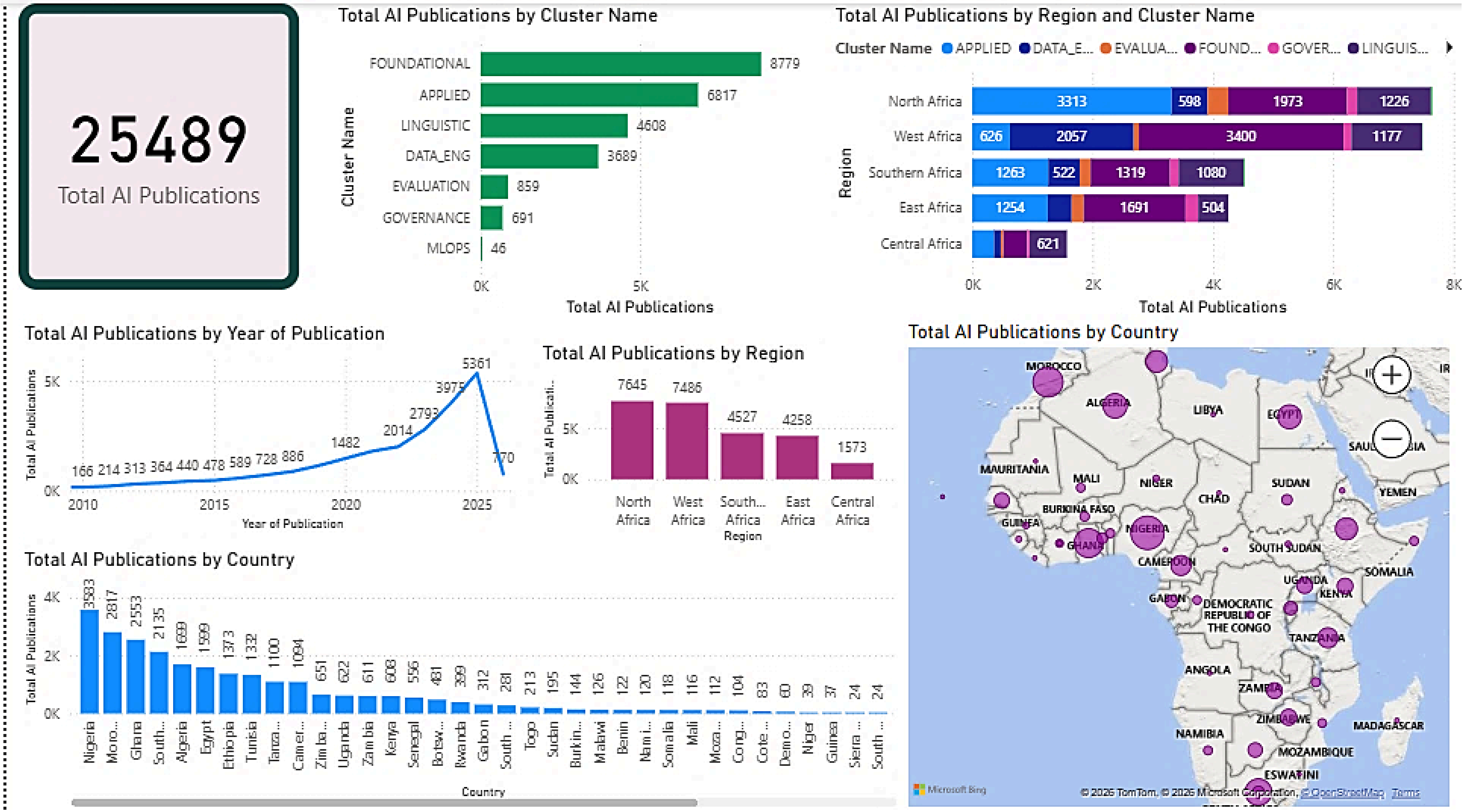


Figure 11: Overview of AI Knowledge Production (Research Publications)

6.1 Regional distribution of AI Research Outputs

AI research production across Africa is **highly regionally concentrated**, with knowledge generation dominated by two leading sub-regions. Figure 12 shows the regional distribution of AI Research Outputs.

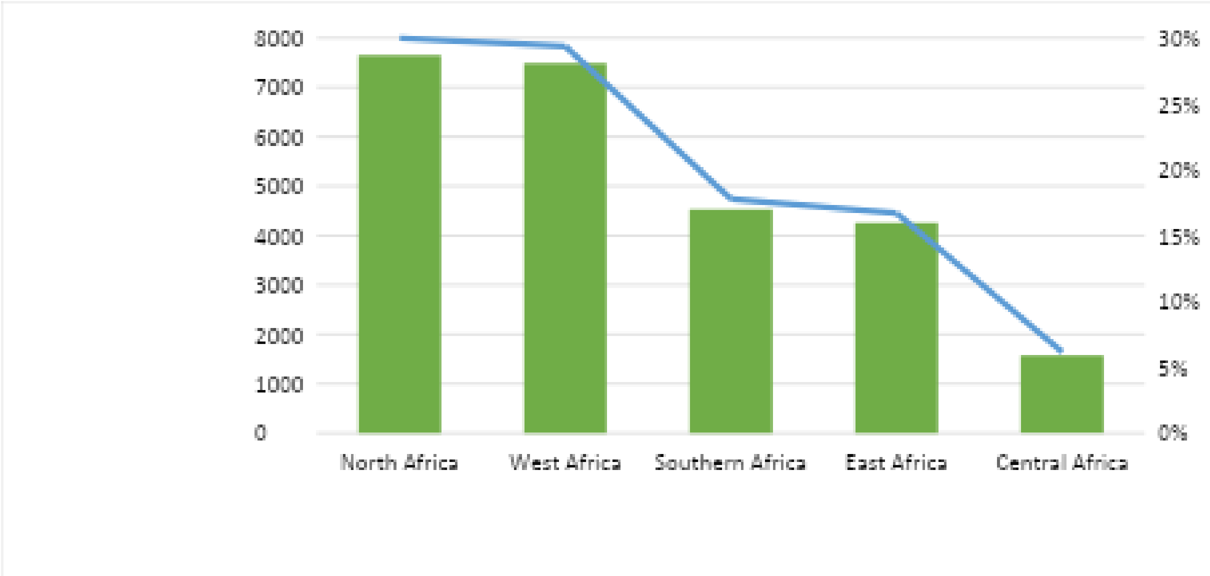


Figure 12: Regional distribution of AI Research Outputs

North Africa (29.99%) and **West Africa (29.37%)** together account for nearly **60% of all AI publications**, indicating strong dual leadership in continental AI knowledge production. These two regions clearly function as Africa's primary research hubs. Their near-equal shares suggest parallel research strength, rather than dominance by a single region. This pattern contrasts with the labour market structure, where North Africa showed stronger singular dominance. In research output, leadership is more balanced between North and West Africa.

A second tier consists of **Southern Africa (17.76%)** and **East Africa (16.71%)**. Together, these regions contribute roughly one-third of total publications. Their output is substantial but clearly below the leading pair, indicating moderate research capacity and institutional development.

Central Africa (6.17%) remains significantly underrepresented in AI knowledge production. Its share is far below all other regions, suggesting limited research infrastructure, lower institutional concentration, or reduced integration into global AI research networks.

Overall, AI research production in Africa is **geographically concentrated but not entirely monopolized**. The market structure shows strong dual leadership (North and West Africa), a mid-level research tier (Southern and East Africa), and a small peripheral contributor (Central Africa). This indicates that knowledge production is clustered, with clear regional research ecosystems driving continental AI scholarship.

6.2 Distribution of AI research by Country

Figure 13 shows the distribution of AI research by Country. From the results, AI knowledge production across Africa is **highly concentrated in a small number of leading countries**, with the top five contributors accounting for a substantial share of total publications.

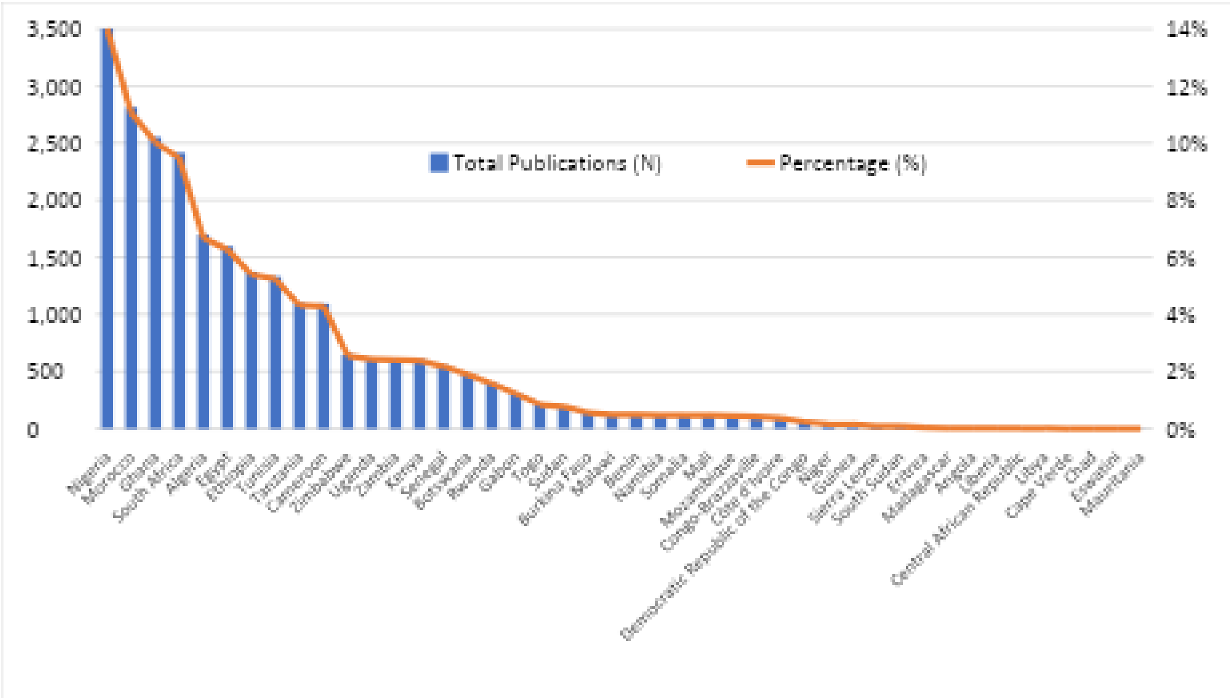


Figure 13: Distribution of AI research by Country

The clear leader is **Nigeria**, producing **3,583 publications (14.06%)**, making it the dominant AI research hub on the continent. It is followed by **Morocco** with **2,817 (11.05%)**, and **Ghana** with **2,553 (10.02%)**. These three countries alone contribute over one-third of Africa's total AI research output.

Next, **South Africa** ranks fourth with **2,416 publications (9.48%)**, reinforcing its role as a major research centre. The top five also include **Algeria** with **1,699 (6.67%)**. Together, these five countries account for nearly **51% of all AI publications in Africa**, indicating strong national-level concentration of research capacity.

A second tier of influential research producers includes **Egypt (6.27%)**, **Ethiopia (5.39%)**, **Tunisia (5.23%)**, and **Tanzania (4.32%)**. These countries demonstrate meaningful but comparatively moderate research output, forming an important mid-level knowledge base.

Beyond these leaders, research output becomes increasingly fragmented. Most remaining countries individually contribute less than 3% of total publications, indicating a long tail of smaller research systems with limited but present AI activity. At the very bottom of the distribution, several countries contribute less than 0.1%, reflecting minimal representation in the dataset.

Overall Conclusion:

AI knowledge production in Africa is **strongly concentrated in Nigeria, Morocco, Ghana, and South Africa**, which together form the continent's primary research engines. While many countries participate in AI scholarship, a relatively small group of nations dominates output, indicating significant disparities in research infrastructure, institutional capacity, and academic ecosystem development across the continent.

6.3 AI Knowledge Research in Africa by Skills Clusters

Figure 14 displays the AI Knowledge Research in Africa by Skills Clusters. AI research production across Africa is strongly oriented toward **core technical knowledge**, with clear dominance of foundational scientific work over deployment-oriented or governance-focused research.

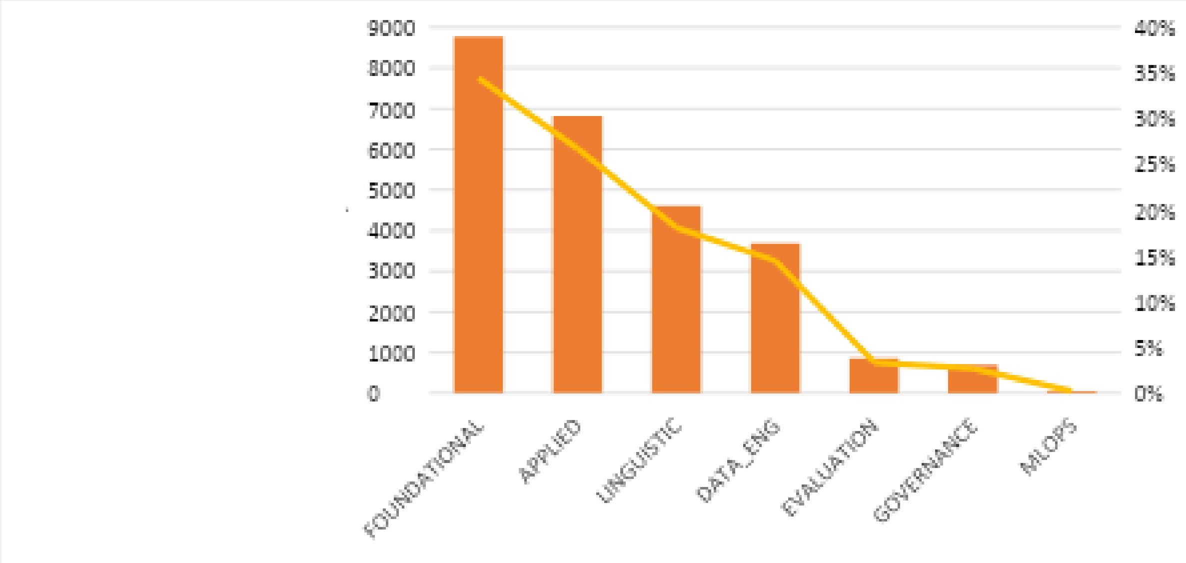


Figure 14: AI Knowledge Research in Africa by Skills Clusters

The most researched cluster is **FOUNDATIONAL AI**, accounting for **8,779 publications (34.44%)**. This indicates that a significant portion of Africa's AI scholarship focuses on fundamental algorithms, theoretical development, model design, and core machine learning methodologies. Foundational research clearly forms the backbone of the continent's AI knowledge production.

The second largest category is **APPLIED AI**, with **6,817 publications (26.74%)**. This substantial share suggests strong engagement in real-world applications of AI across sectors such as health, agriculture, finance, education, and industry. The prominence of applied research indicates that African AI scholarship is not purely theoretical but also strongly practice-oriented.

LINGUISTIC AI represents **4,608 publications (18.08%)**, reflecting significant research in natural language processing, multilingual systems, and language technologies. Given Africa's linguistic diversity, this relatively high share highlights the importance of language-focused AI innovation on the continent.

DATA ENGINEERING accounts for **3,689 publications (14.47%)**, demonstrating meaningful attention to data infrastructure, data processing, and system architecture. This suggests growing recognition of the importance of data readiness in enabling AI systems.

In contrast, research in **EVALUATION** (859 publications; **3.37%**) and **GOVERNANCE** (691 publications; **2.71%**) remains comparatively limited. While these areas are essential for responsible AI development, their lower share indicates that regulatory, ethical, and performance-assessment research is still emerging relative to technical development.

Finally, **MLOps** is the least researched cluster, with only **46 publications (0.18%)**, suggesting that operationalization, deployment scaling, and production-level AI engineering remain underrepresented in Africa's academic research landscape.

The above finings demonstrate that the structure of AI knowledge production in Africa is **strongly technically oriented**, with over **75% of publications concentrated in Foundational and Applied AI combined**. Governance, evaluation, and MLOps collectively represent a very small share of research output. This indicates that Africa's AI research ecosystem prioritizes innovation and development, while policy-oriented and deployment-focused research remains comparatively limited.

6.4 AI Knowledge Publications by Sub-Region in each Skill Cluster

Figure 15 visualises the AI Knowledge Publications by Sub-Region in each Skill Cluster

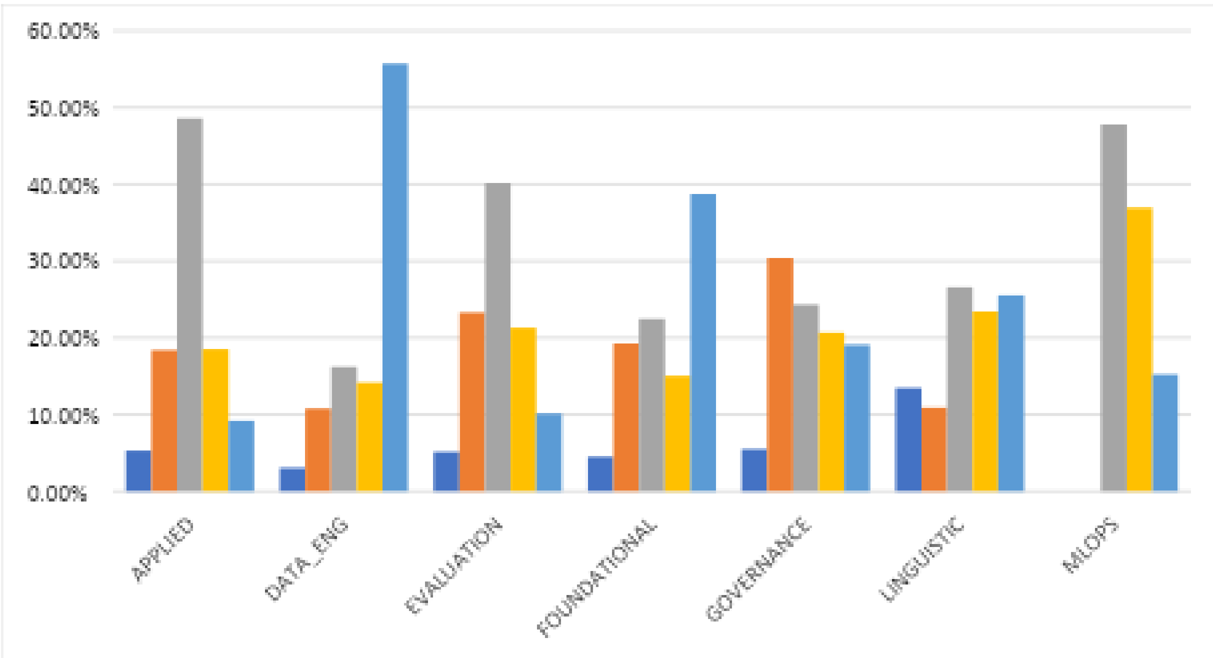


Figure 15: AI Knowledge Publications by Sub-Region in each Skill Cluster

FOUNDATIONAL AI (8,779 publications): This is the largest AI knowledge cluster in Africa. Leadership is clearly held by **West Africa**, contributing **3,400 publications (38.73%)**, making it the dominant research hub in core AI theory and model development. It is followed by **North Africa (22.47%)** and **East Africa (19.26%)**, while Southern Africa contributes 15.02%. Central Africa remains marginal (4.51%). Foundational AI is therefore strongly West African-led.

APPLIED AI (6,817 publications): Applied AI is the second-largest cluster and is overwhelmingly dominated by **North Africa**, which produces **3,313 publications (48.60%)**, nearly half of all applied research. **Southern Africa (18.53%)** and **East Africa (18.40%)** form a secondary tier. West Africa contributes 9.18%, while Central Africa contributes 5.30%. Applied AI research is thus highly concentrated in North Africa.

LINGUISTIC AI (4,608 publications): Linguistic AI shows relatively balanced distribution but is led by **North Africa (26.61%)**, closely followed by **West Africa (25.54%)** and **Southern Africa (23.44%)**. East Africa contributes 10.94%, while Central Africa has a comparatively notable 13.48%. Unlike other clusters, Linguistic AI is more geographically dispersed across regions.

DATA ENGINEERING (3,689 publications): Data Engineering research is decisively led by **West Africa**, which contributes **2,057 publications (55.76%)**, more than half of total output in this cluster. North Africa (16.21%) and Southern Africa (14.15%) follow at a distance, while East Africa (10.82%) and Central Africa (3.06%) contribute modestly. This cluster reflects strong West African specialization.

EVALUATION (859 publications): Evaluation research is led by **North Africa**, accounting for **345 publications (40.16%)**. East Africa (23.28%) and Southern Africa (21.30%) follow, forming a competitive secondary tier. West Africa contributes 10.13%, and Central Africa 5.12%. While smaller in volume, this cluster shows broader regional participation compared to Data Engineering.

GOVERNANCE (691 publications): Governance research is led by **East Africa**, contributing **210 publications (30.39%)**, making it the primary hub for AI ethics, regulation, and policy scholarship. North Africa (24.31%), Southern Africa (20.69%), and West Africa (19.10%) follow closely. This is one of the more evenly distributed clusters despite its smaller size.

MLOps (46 publications): MLOps is the smallest cluster and is highly concentrated. **North Africa leads (47.83%)**, followed by **Southern Africa (36.96%)** and **West Africa (15.22%)**. Central and East Africa show no recorded contributions. This cluster remains underdeveloped continent-wide.

6.5 AI Knowledge Publications by Country in each Skill Cluster

Figure 16 is a heatmap showing the distribution of AI Knowledge Publications by Country in each Skill Cluster.

Country	APPLIED	DATA_ENG	EVALUATION	FOUNDATIONAL	GOVERNANCE	LINGUISTIC	MLOPS
Algeria	10.88%	1.95%	8.03%	3.92%	2.89%	9.74%	6.52%
Angola	0.00%	0.11%	0.00%	0.00%	0.00%	0.00%	0.00%
Benin	0.01%	1.33%	0.12%	0.75%	0.00%	0.11%	0.00%
Botswana	0.17%	1.71%	3.38%	2.25%	1.01%	3.76%	0.00%
Burkina Faso	0.04%	1.46%	0.00%	0.93%	0.00%	0.11%	0.00%
Cameroon	4.24%	1.60%	3.84%	2.68%	4.63%	9.68%	0.00%
Cape Verde	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%
Central African Republic	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.00%
Chad	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%
Congo-Brazzaville	0.00%	1.27%	0.00%	0.56%	0.00%	0.17%	0.00%
Côte d'Ivoire	0.32%	0.30%	0.12%	0.37%	0.00%	0.58%	0.00%
DRC	0.10%	0.03%	0.00%	0.49%	0.87%	0.07%	0.00%
Egypt	9.43%	5.34%	6.17%	5.73%	4.92%	3.62%	4.35%
Eritrea	0.00%	0.19%	0.00%	0.08%	0.00%	0.00%	0.00%
Eswatini	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%
Ethiopia	4.94%	2.60%	3.38%	7.39%	6.22%	4.75%	0.00%
Gabon	0.95%	0.08%	1.28%	0.79%	0.00%	3.56%	0.00%
Ghana	2.45%	20.25%	3.61%	11.93%	8.97%	10.81%	2.17%
Guinea	0.01%	0.30%	0.00%	0.23%	0.00%	0.11%	0.00%
Kenya	2.20%	2.82%	4.89%	2.55%	3.76%	1.35%	0.00%
Liberia	0.00%	0.03%	0.00%	0.03%	0.00%	0.00%	0.00%
Libya	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.00%
Madagascar	0.00%	0.00%	0.00%	0.05%	0.00%	0.02%	0.00%
Malawi	0.01%	1.33%	0.12%	0.75%	0.00%	0.20%	0.00%
Mali	0.00%	1.82%	0.12%	0.43%	0.00%	0.22%	0.00%
Mauritania	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%
Morocco	20.51%	3.53%	20.25%	7.01%	10.85%	8.98%	21.74%
Mozambique	0.00%	1.41%	0.12%	0.57%	0.00%	0.20%	0.00%
Namibia	0.04%	1.52%	0.23%	0.54%	0.00%	0.26%	0.00%
Niger	0.00%	0.60%	0.00%	0.19%	0.00%	0.00%	0.00%
Nigeria	4.18%	26.43%	3.61%	21.34%	7.38%	7.85%	10.87%
Rwanda	0.19%	1.73%	3.03%	2.56%	2.89%	1.11%	0.00%
Senegal	2.14%	0.43%	2.56%	1.30%	2.75%	5.19%	0.00%
Sierra Leone	0.00%	0.22%	0.00%	0.14%	0.00%	0.09%	0.00%
Somalia	0.00%	1.60%	0.12%	0.58%	0.00%	0.15%	0.00%
South Africa	11.80%	4.72%	6.75%	6.91%	13.17%	14.41%	36.96%
South Sudan	0.01%	0.35%	0.00%	0.08%	0.00%	0.07%	0.00%

Country	APPLIED	DATA_ENG	EVALUATION	FOUNDATIONAL	GOVERNANCE	LINGUISTIC	MLOPS
Sudan	0.01%	2.17%	0.00%	1.08%	0.14%	0.39%	0.00%
Tanzania	7.57%	1.27%	6.29%	3.37%	11.58%	2.32%	0.00%
Togo	0.01%	2.60%	0.00%	1.06%	0.00%	0.48%	2.17%
Tunisia	7.76%	3.14%	5.70%	4.73%	5.50%	3.86%	15.22%
Uganda	3.48%	0.24%	5.59%	2.64%	5.93%	1.19%	0.00%
Zambia	2.95%	1.52%	5.94%	1.63%	2.60%	3.08%	0.00%
Zimbabwe	3.54%	1.84%	4.77%	2.34%	3.91%	1.50%	0.00%
%	100%	100%	100%	100%	100%	100%	100%
Total (N)	6817	3689	859	8779	691	4608	46

Figure 16: AI Knowledge Publications by Country in each Skill Cluster

FOUNDATIONAL AI (8,779 publications): Foundational AI is the largest research domain in Africa. The clear leader is **Nigeria**, contributing **1,874 publications (21.34%)**, giving it a commanding position in core AI theory and model development. It is followed by **Ghana (1,047; 11.93%)**, and then **Ethiopia (649; 7.39%)**, **Morocco (616; 7.01%)**, and **South Africa (607; 6.91%)**. Together, these five countries account for more than half of all foundational AI research, demonstrating strong concentration in West and North Africa, with important contributions from Southern and East Africa.

APPLIED AI (6,817 publications): Applied AI is led decisively by **Morocco**, which produces **1,398 publications (20.51%)**, making it the continental leader in real-world AI applications. It is followed by **South Africa (805; 11.80%)**, **Algeria (742; 10.88%)**, and **Egypt (643; 9.43%)**. A strong emerging contributor is **Tanzania (516; 7.57%)**, while **Tunisia (7.76%)** also plays a notable role. Applied AI research is therefore heavily concentrated in North Africa and Southern Africa.

LINGUISTIC AI (4,608 publications): Linguistic AI research is led by **South Africa**, contributing **664 publications (14.41%)**, reflecting strong expertise in language technologies. It is closely followed by **Ghana (498; 10.81%)**, **Algeria (449; 9.74%)**, and **Cameroon (446; 9.68%)**. **Morocco (8.98%)** and **Nigeria (7.85%)** also make significant contributions. Unlike other clusters, Linguistic AI leadership is more distributed across multiple countries, reflecting Africa's multilingual research needs.

DATA ENGINEERING (3,689 publications): Data Engineering is overwhelmingly dominated by **Nigeria**, which contributes **975 publications (26.43%)**, far ahead of all other countries. The second-largest contributor is **Ghana (747; 20.25%)**, followed by **Egypt (197; 5.34%)** and

South Africa (174; 4.72%). This cluster is therefore strongly West African-led, with Nigeria and Ghana jointly accounting for nearly half of all Data Engineering research.

EVALUATION (859 publications): Evaluation research is led by **Morocco**, contributing **174 publications (20.25%)**, making it the dominant country in model assessment and validation studies. It is followed by **Algeria (69; 8.03%)**, **South Africa (58; 6.75%)**, and **Tanzania (54; 6.29%)**. Other notable contributors include **Egypt (6.17%)**, **Tunisia (5.70%)**, and **Zambia (5.94%)**. Although smaller in size, Evaluation research shows relatively broader national participation.

GOVERNANCE (691 publications): Governance research is led by **South Africa**, which produces **91 publications (13.17%)**, making it the strongest contributor in AI ethics and policy scholarship. It is followed by **Tanzania (80; 11.58%)**, **Morocco (75; 10.85%)**, and **Ghana (62; 8.97%)**. **Nigeria (7.38%)** and **Tunisia (5.50%)** also contribute meaningfully. Governance research is more evenly distributed across leading countries compared to highly technical clusters.

MLOps (46 publications): MLOps is the smallest cluster and is highly concentrated. **South Africa** leads overwhelmingly with **17 publications (36.96%)**. It is followed by **Morocco (10; 21.74%)** and **Tunisia (7; 15.22%)**. **Nigeria (10.87%)** and **Algeria (6.52%)** contribute smaller shares. MLOps research remains underdeveloped continent-wide and is concentrated in a few technically advanced ecosystems.

Overall Structural Pattern

When ordered from largest to smallest clusters, **Nigeria** dominates Foundational and Data Engineering, while **Morocco** dominates Applied and Evaluation. Similarly, **South Africa** dominates Linguistic AI and MLOps, while **South Africa and Tanzania** play key roles in Governance. This demonstrates clear **country-level specialization by AI knowledge domain**, with leadership varying depending on the type of research. Africa's AI knowledge ecosystem is therefore not only concentrated but also structurally differentiated by national strengths.

6.6 Annual Distribution of AI Knowledge Publications in Africa

Figure 17 shows the Annual Distribution of AI Knowledge Publications in Africa. AI knowledge production across Africa demonstrates a highly concentrated temporal pattern, with the overwhelming majority of publications generated in the last decade.

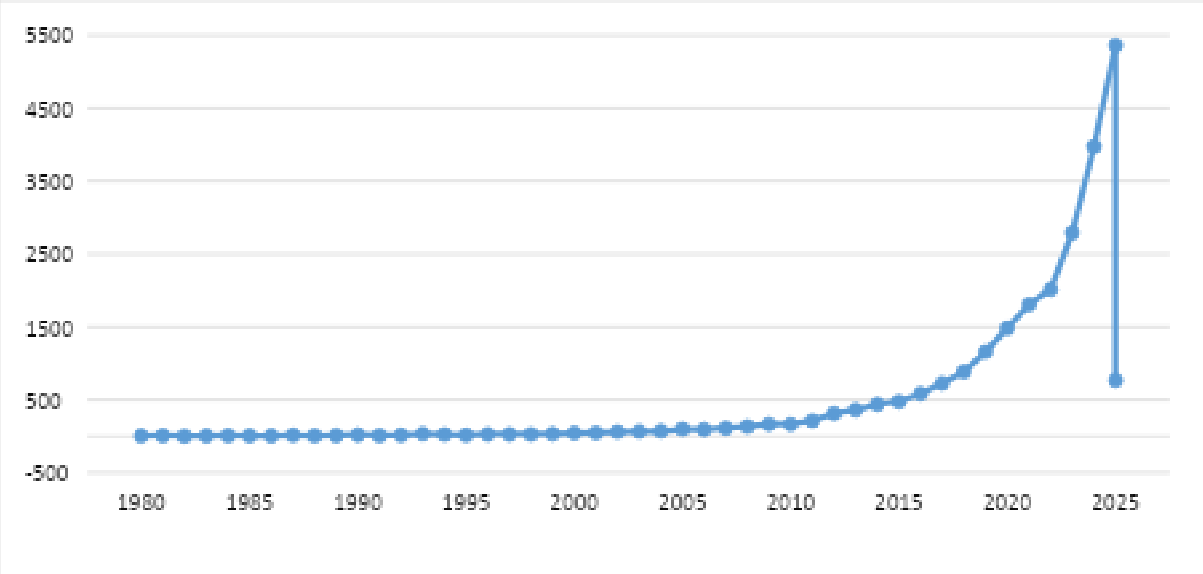


Figure 17: Annual Distribution of AI Knowledge Publications in Africa

From 1980 through the late 1990s, research output was minimal and irregular, with annual publications remaining in very low double-digit figures. This period reflects the early developmental stage of AI scholarship on the continent, characterized by limited institutional capacity, constrained research infrastructure, and relatively low integration into global AI research networks. During these years, AI activity existed but did not represent a significant scholarly movement.

Between 2000 and 2010, Africa's AI research ecosystem entered a gradual growth phase. Publication counts increased steadily, rising from fewer than 50 publications per year at the beginning of the decade to more than 160 by 2010. Although this growth was consistent, it remained moderate, indicating early consolidation rather than large-scale expansion. This period can be interpreted as the foundation-building stage of AI scholarship, where awareness, capacity development, and initial research networks began to form more systematically across the continent.

A more pronounced acceleration became visible between 2011 and 2018. During this phase, annual publications increased substantially, moving from just over 200 in 2011 to nearly 900 by 2018. This represents a several-fold increase within a relatively short timeframe, signaling the beginning of structural transformation in Africa's AI research landscape. The growth during this period aligns with global advancements in machine learning and increased digital adoption, which likely contributed to expanding research engagement within African institutions.

The most significant transformation occurs from 2019 onward, where AI knowledge production enters an exponential growth trajectory. Publication output rises dramatically year after year, increasing from 1,159 in 2019 to 5,361 in 2025. This rapid expansion demonstrates strong institutionalization of AI research across multiple countries and sub-regions. The magnitude of growth during this period far exceeds earlier decades, indicating that Africa's AI research ecosystem is currently in a rapid scaling phase rather than a mature or stabilized stage. The year 2025 represents the peak annual output in the dataset, reflecting the height of this expansion cycle.

Although 2026 shows a lower figure, this is most likely attributable to partial-year data rather than an actual decline in research activity. Therefore, the overall trend remains strongly upward, particularly in the most recent years. The data clearly demonstrate that the majority of Africa's AI knowledge production has occurred after 2015, with the most dramatic acceleration taking place between 2019 and 2025.

In summary, AI knowledge production in Africa is highly time-concentrated in the modern period, especially the last decade. The pattern reflects a late but rapidly accelerating entry into global AI research dynamics. Rather than showing long-term stability, the data reveal exponential growth, indicating that Africa's AI research ecosystem is currently in an expansionary and transformative phase.

6.7 Annual Distribution of AI Knowledge Publications across African Regions

Figure 18 shows the annual distribution of AI Knowledge Publications across African Regions. There is a **clear time concentration and distinct regional growth patterns** in AI knowledge production across Africa.

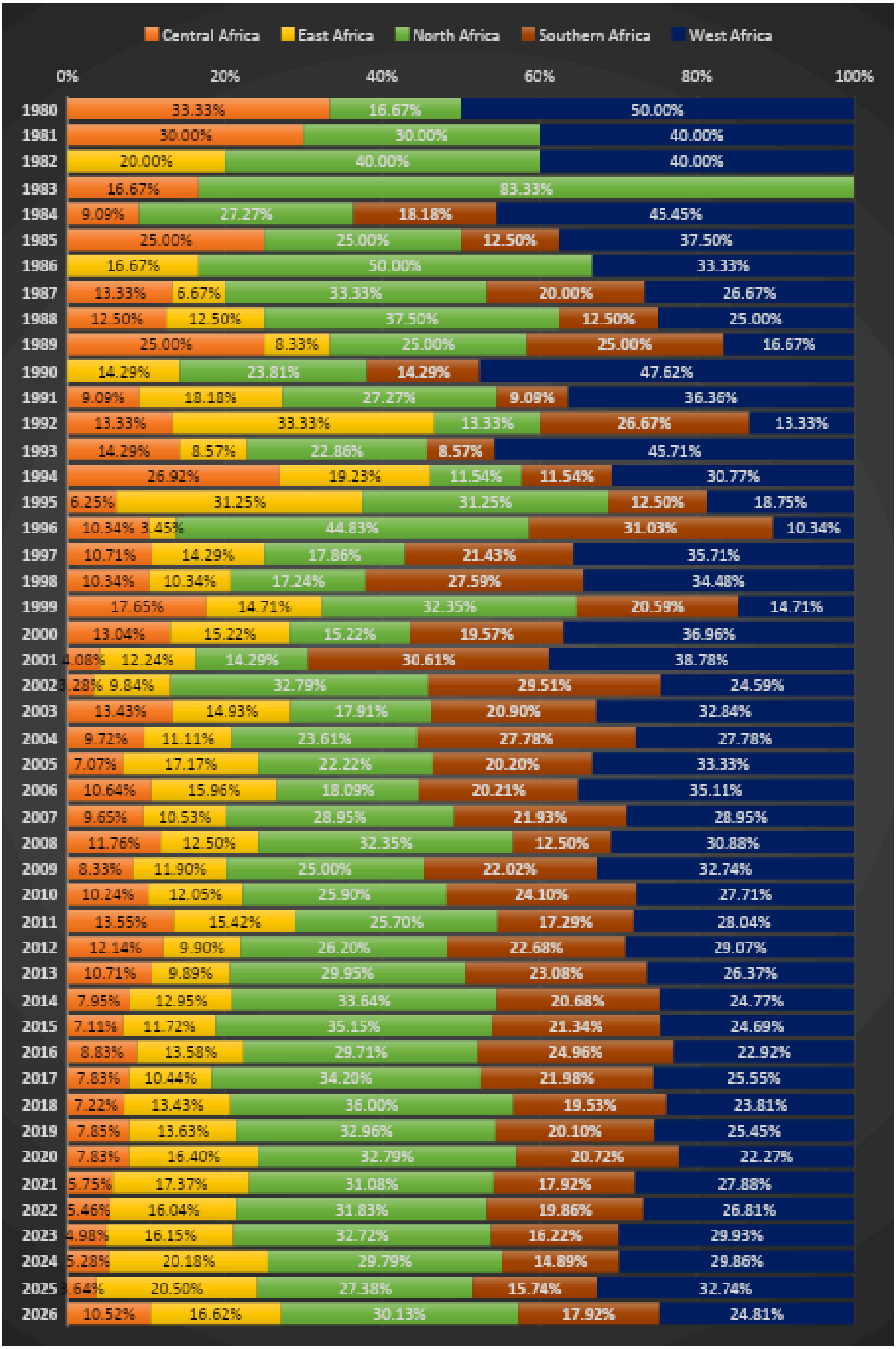


Figure 18: Annual Distribution of AI Knowledge Publications across African Regions

North Africa: North Africa shows the **strongest and most sustained growth trend** over time. Its output increases steadily from very low levels in the 1980s to dominant levels after 2010. By 2018, North Africa contributes **319 publications (36.00%)**, and in 2025 it reaches **1,468 publications (27.38%)**, representing one of the highest absolute annual totals in the dataset. Throughout the post-2010 period, North Africa consistently accounts for roughly **27–36% of annual publications**, demonstrating stable regional leadership in AI research. The pattern indicates **long-term structural dominance**, especially in the most recent decade, where North Africa remains one of the top contributors every year.

West Africa: West Africa exhibits a **strong upward growth trajectory**, particularly after 2010. In early years, its contribution fluctuates, but from 2015 onward it becomes one of the dominant regions. In 2024 and 2025, West Africa records **1,187 publications (29.86%)** and **1,755 publications (32.74%)**, respectively — making it the leading region in 2025. This shows a **clear acceleration pattern**, with West Africa emerging as a major research hub in the last decade. Its contribution has remained consistently high (approximately 24–33%) in recent years, indicating sustained expansion rather than short-term spikes.

East Africa: East Africa demonstrates **gradual but accelerating growth**, particularly after 2015. Its share rises significantly in the recent period. In 2024, it contributes **802 publications (20.18%)**, and in 2025 it increases to **1,099 publications (20.50%)**. Although it does not dominate any single year, East Africa shows a **steady upward trend in both volume and share**, especially since 2018. Its contribution typically ranges between **10% and 20% annually**, reflecting consistent expansion and strengthening research capacity.

Southern Africa: Southern Africa also shows long-term growth but with slightly more moderate expansion compared to North and West Africa. Its annual share generally ranges between **14% and 25%** in recent years. In 2024, it records **592 publications (14.89%)**, and in 2025 it rises to **844 publications (15.74%)**. While not the dominant region, Southern Africa maintains a **stable secondary-tier contribution**, particularly strong during the mid-2010s expansion period. Its trend reflects steady development rather than sharp acceleration.

Central Africa: Central Africa remains the **smallest contributor throughout the entire period**. Although it shows gradual increases in absolute numbers, its annual share generally remains below **10%**, often closer to **5–8%** in recent years. In 2025, it contributes **195**

publications (3.64%), indicating relatively limited expansion compared to other regions. The pattern suggests **structural underrepresentation**, with no strong long-term growth trajectory comparable to the other regions.

6.7.1 Overall Regional Trend Analysis

The data clearly demonstrate that AI knowledge production in Africa is **highly time-concentrated**, especially after 2010 and most intensely after 2019. All regions experience growth, but the expansion is **uneven**. North Africa and West Africa exhibit the strongest long-term dominance. West Africa shows particularly rapid acceleration in the most recent years, while North Africa maintains consistent leadership across most of the modern period.

East and Southern Africa display steady upward trends, forming a strong secondary research tier. Central Africa remains comparatively limited, with no major shift in its structural position. In conclusion, AI research growth in Africa is not only increasing over time but also **regionally differentiated**, with clear patterns of leadership, consolidation, and emerging expansion.

6.8 Annual Distribution of AI Knowledge Publications across each Knowledge cluster

Figure 19 displays the annual distribution of AI Knowledge Publications across each Knowledge cluster in Africa. There is a very clear temporal pattern in how each AI knowledge cluster contributes annually across Africa. The data show not only rapid overall growth, but also structural shifts in cluster composition over time.

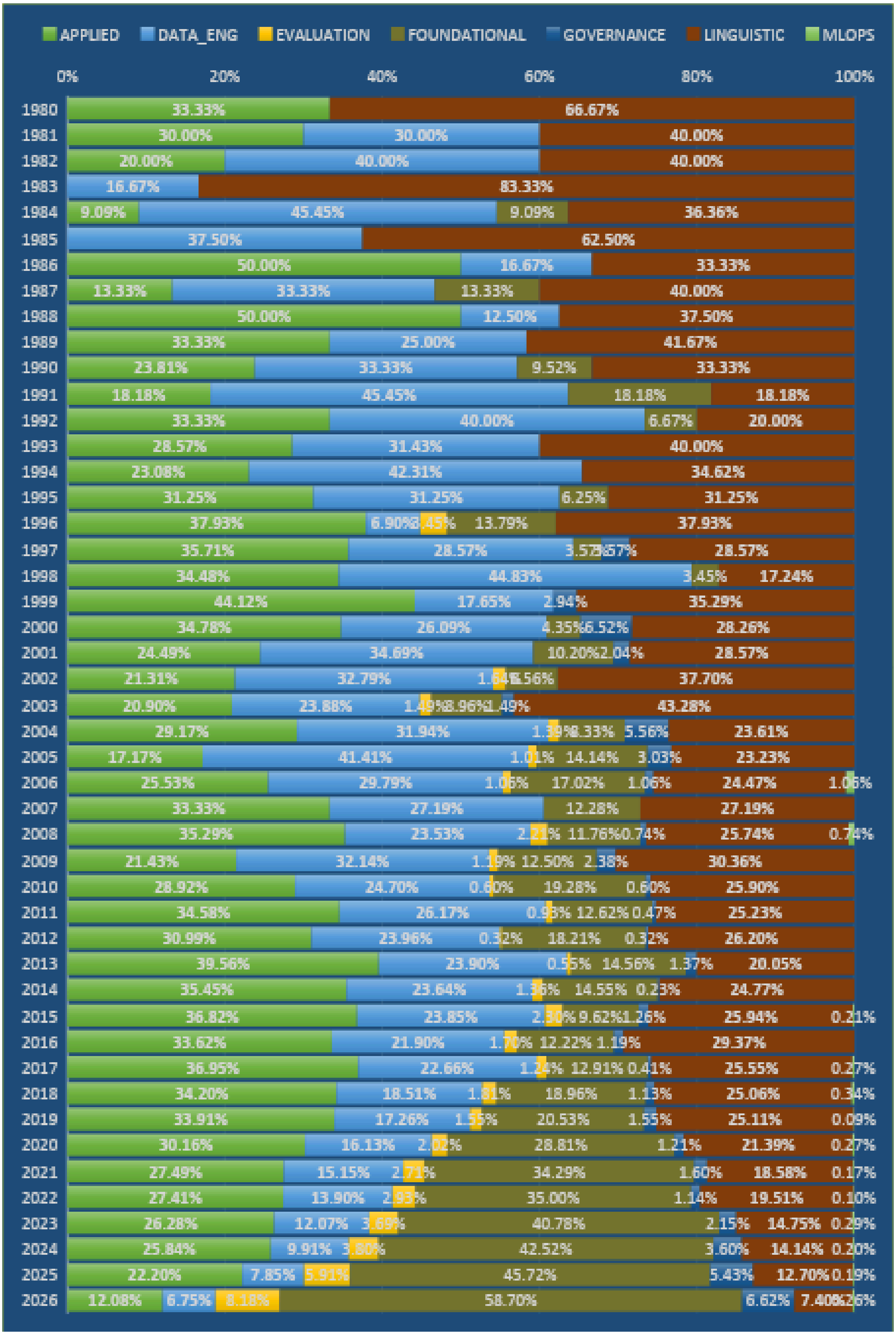


Figure 19: Annual Distribution of AI Knowledge Publications across each Knowledge cluster in Africa

Foundational AI has become the dominant cluster in recent years. Its growth is especially pronounced after 2015. For example, it rises from **705 publications (35.00%) in 2022** to **1,139 (40.78%) in 2023**, then **1,690 (42.52%) in 2024**, and peaks at **2,451 publications (45.72%) in 2025**. This shows a consistent upward trend in both volume and proportional share. Over time, Foundational AI transitions from a mid-level contributor in the early years to the **leading structural pillar** of Africa's AI research ecosystem. Its increasing percentage share indicates not just growth in absolute terms, but also growing dominance relative to other clusters.

Applied AI shows steady growth in absolute numbers, particularly from 2015 onward. It increases from **552 publications (27.41%) in 2022** to **734 (26.28%) in 2023**, and then to **1,027 (25.84%) in 2024**. Although its absolute output rises, its **percentage share gradually declines** in recent years. This suggests that while Applied AI continues to expand numerically, it is growing more slowly than Foundational AI. Therefore, its relative dominance is decreasing, indicating a structural shift toward deeper theoretical research.

Data Engineering demonstrates strong early growth but a declining proportional trend in recent years. For example, it records **280 publications (13.90%) in 2022**, then **337 (12.07%) in 2023**, and **394 (9.91%) in 2024**. Although absolute numbers increase, its share steadily declines. This pattern indicates that Data Engineering, while expanding, is not keeping pace with the rapid acceleration of Foundational AI. It remains important but is gradually losing relative weight within the research ecosystem.

Linguistic AI shows consistent but moderate growth. Its share remains relatively stable in earlier years (around 20–30%), but in recent years it declines proportionally — for example, **19.51% in 2022**, **14.75% in 2023**, **14.14% in 2024**, and **12.70% in 2025**. Despite this proportional decline, absolute numbers continue increasing. This suggests that Linguistic AI is growing, but at a slower rate compared to Foundational AI, leading to reduced relative dominance over time.

Evaluation research shows a clear upward trend in both absolute and relative terms. It rises from **59 publications (2.93%) in 2022** to **103 (3.69%) in 2023**, **151 (3.80%) in 2024**, and **317 (5.91%) in 2025**. Unlike Data Engineering and Linguistic AI, Evaluation is **gaining share**, indicating increasing attention to model validation, benchmarking, and performance assessment. This reflects growing maturity in the research ecosystem.

Governance also shows steady proportional growth. It increases from **23 publications (1.14%) in 2022** to **60 (2.15%) in 2023**, **143 (3.60%) in 2024**, and **291 (5.43%) in 2025**. This strong upward trend suggests that ethical, regulatory, and policy-related AI research is becoming increasingly important. Governance is one of the fastest-growing clusters in relative terms, indicating maturation of the AI ecosystem.

MLOps remains the smallest cluster throughout the entire period. Although it increases slightly in absolute terms in recent years, its share remains below **1% in most years**, reaching only **0.19% in 2025** and **0.26% in 2026**. This indicates that operational deployment and production-scale AI engineering are still underdeveloped in Africa's research landscape.

6.8.1 Overall Cluster Trend Pattern

- The annual structure of AI knowledge production in Africa reveals a clear transformation. In early decades, research was distributed more evenly across clusters. However, since 2015 — and especially after 2019 — the system has shifted decisively toward **Foundational AI dominance**.
- Foundational AI is increasing both in absolute numbers and percentage share, demonstrating structural centralization. Evaluation and Governance are also rising in proportional importance, suggesting increasing ecosystem maturity. Meanwhile, Applied, Data Engineering, and Linguistic AI continue to grow in volume but are gradually declining in relative share.
- Overall, the pattern shows a **structural transition toward deeper theoretical research combined with increasing governance awareness**, while deployment-focused areas such as MLOps remain limited. The growth trend is therefore not only rapid but also compositionally shifting across knowledge domains.

6.9 Overall AI Knowledge Publications Across Africa

Based on the full set of analyses across Africa, the evidence shows that AI knowledge production is **concentrated in structure but expanding in scale**. Below is a synthesis supported by the observed data. Overall output totals **25,489 publications**, with a strong acceleration occurring after 2010 and especially after 2019. Annual production rises from modest levels in the 1980s and 1990s (generally below 50 per year) to **5,361 publications in 2025**, representing the peak of the observed period. This indicates that AI knowledge production is not stagnant; rather, it is experiencing **rapid exponential growth**, particularly in the last decade.

6.9.1. Regional Concentration

Regionally, research is **highly concentrated in two sub-regions**. **North Africa (29.99%)** and **West Africa (29.37%)** together account for approximately **59% of total publications**. The next tier consists of **Southern Africa (17.76%)** and **East Africa (16.71%)**, while **Central Africa contributes only 6.17%**. This distribution clearly indicates **regional concentration**, with two dominant hubs driving most of the continent's AI scholarship.

6.9.2 Country Concentration

At the country level, concentration is even more pronounced. The top five countries — **Nigeria (14.06%)**, **Morocco (11.05%)**, **Ghana (10.02%)**, **South Africa (9.48%)**, and **Algeria (6.67%)** — collectively account for **over 51% of total AI publications**. This means that a small group of countries dominates knowledge production, while many others contribute comparatively small shares (often below 3%). Therefore, the country distribution is **strongly concentrated**, not evenly distributed.

6.9.3. Skill (Knowledge Cluster) Concentration

AI research is also **cluster-concentrated**. The largest cluster is **Foundational AI (34.44%)**, followed by **Applied AI (26.74%)**. Together, these two clusters represent **over 61% of total publications**. The remaining clusters — Linguistic (18.08%), Data Engineering (14.47%), Evaluation (3.37%), Governance (2.71%), and MLOps (0.18%) — collectively account for less than 40%. This indicates that AI research is heavily focused on core technical domains, with relatively limited emphasis on governance, evaluation, and deployment (MLOps). The knowledge structure is therefore **technically concentrated**.

6.9.4 Is Research Impact Growing or Flat? (Temporal Trend)

The temporal analysis shows a **clear exponential growth pattern**, not stagnation. Annual publications increase from single-digit levels in the 1980s to thousands per year in the 2020s. The most dramatic expansion occurs between **2019 and 2025**, where annual output rises from **1,159 to 5,361 publications**.

Additionally, regional and cluster data show that growth is sustained across most sub-regions and knowledge domains, especially Foundational AI, Governance, and Evaluation. This indicates that Africa's AI research ecosystem is **rapidly expanding**, not flat or declining.

6.9.5. Overall Conclusion: Concentrated or Broad-Based?

AI Knowledge Publications in Africa are **structurally concentrated but dynamically growing**. They are concentrated geographically (top regions ≈59%; top countries ≈51%), concentrated by skill (top two clusters ≈61%), and concentrated in recent years (post-2019 exponential surge). However, they are **broadening over time in absolute scale**, with all regions and most clusters showing upward trends. Therefore, the system is best described as **concentrated in leadership but expanding in participation**, rather than fully broad-based. Table 5 offers the overall synthesis of AI Knowledge Publications in Africa.

Table 5: Overall Synthesis of AI Knowledge Publications in Africa

Question	Evidence-Based Conclusion (With Statistics)
Who produces AI research?	● Research is primarily produced by a small group of countries. ● The top five contributors — **Nigeria (14.06%)**, **Morocco (11.05%)**, **Ghana (10.02%)**, **South Africa (9.48%)**, and **Algeria (6.67%)** — together account for **over 51% of all publications (25,489 total)**. ● Regionally, leadership is concentrated in **North Africa (29.99%)** and **West Africa (29.37%)**, which jointly contribute about **59%** of total output.
Is it concentrated?	● Yes, the system is highly concentrated. Geographically, the top two regions contribute **~59%** of research. ● At country level, the top five countries contribute **~51%**. ● By skill cluster, the top two domains — **Foundational AI (34.44%)** and **Applied AI (26.74%)** — account for **over 61%** of all publications. ● This demonstrates strong structural concentration across regions, countries, and knowledge types.
What kind of AI?	● Research is predominantly **technical and foundational**. **Foundational AI (8,779 publications; 34.44%)** is the largest cluster, followed by **Applied AI (6,817; 26.74%)**. Together they represent more than **61%** of total output. ● Governance (2.71%) and MLOps (0.18%) remain comparatively small, indicating limited focus on operational deployment and regulatory research relative to core model development.
Is AI research output growing?	● Yes — growth is exponential. Annual publications rise from single digits in the 1980s to **5,361 publications in 2025**, the peak year in the dataset. ● After 2010, and especially post-2019, output accelerates sharply. For example, total annual publications increase from **1,159 (2019)** to **5,361 (2025)**. This confirms rapid and sustained expansion rather than stagnation.

CHAPTER 7: AI CAPABILITY PRODUCTION: OPEN-SOURCE AND DEVELOPER ECOSYSTEMS

This chapter shifts from economic demand and academic production to technical execution. Using 27,349 AI GitHub talent repositories as a proxy for open-source capability production, the chapter assesses where AI systems are actively being built across Africa. The analysis investigates regional and national concentration within the 27,349 repositories, examines the distribution of skill clusters (e.g., Linguistic, Foundational, Applied, MLOps, Governance), and evaluates whether communities are maturing over time. Because the repository total exceeds both job postings and research publications, it provides insight into grassroots developer dynamism and technical experimentation. This chapter answers the question: Where is AI capability being built in Africa, and what does the scale and composition of 27,349 repositories reveal about the continent's developer ecosystem? Figure 20 presents an overview of AI Knowledge/Capability Production (GitHub) in Africa.

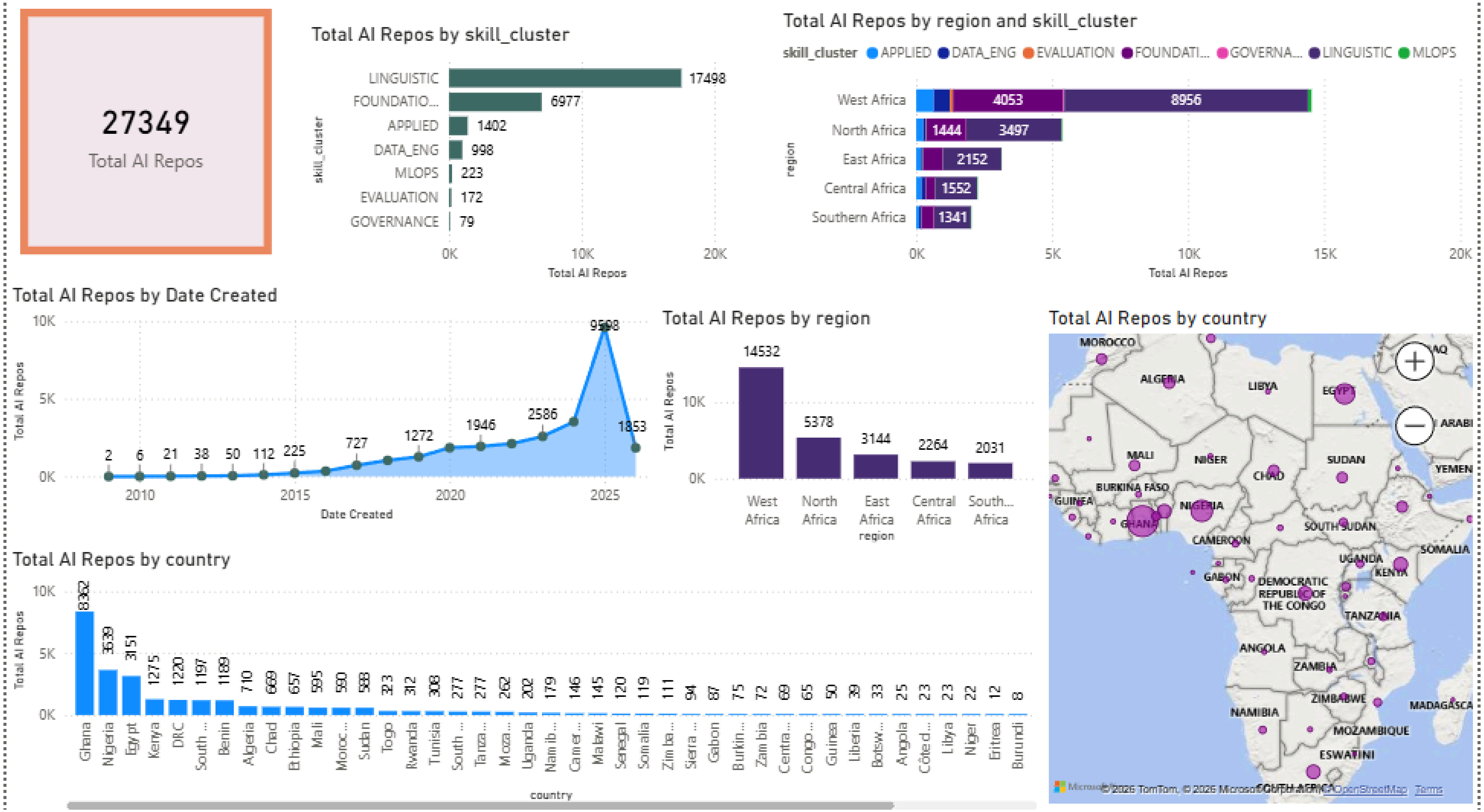


Figure 20: Overview of AI Knowledge/Capability Production (GitHub)

7.1. Regional distribution of AI capability production in Africa

Figure 21 visualises the AI Talent Repositories by Sub-Region. Across Africa's open-source ecosystem, AI capability (measured as GitHub repositories, contributions, and developer activity) is markedly **concentrated in a few sub-regions** rather than evenly distributed.

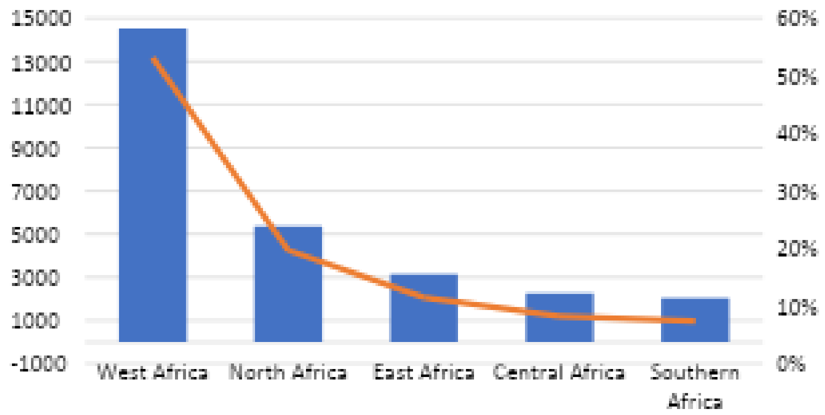


Figure 21: AI Talent Repositories by Sub-Region

West Africa leads by a wide margin with **14,532 repositories (53.14%)** of all African GitHub AI contributions, while **North Africa** follows with **5,378 (19.66%)**, forming the second-largest cluster of open-source AI activity. Also, **East Africa** contributes **3,144 (11.50%)**, showing solid participation but far below the West and North, while **Central Africa** (2,264; 8.28%) and **Southern Africa** (2,031; 7.43%) contribute smaller portions of the overall capability pool. The total across all regions is **27,349 contributions (100%)**.

West Africa's dominant share reflects a **rapidly expanding developer ecosystem**, particularly in countries such as Nigeria and Ghana. According to global GitHub growth data, Nigerian developers alone number over 1.1 million and are growing rapidly year-over-year, with strong increases tied to AI, Python, and open source contributions[1].

This dominance is likely due to a combination of factors:

- Large and youthful population with strong mobile and internet adoption.
- Rapid growth of programming culture and open source communities, especially around AI and machine learning technologies.
- Developer skilling programs (e.g., **GitHub's GenAI for Youth**) that actively engage Nigerian, Ghanaian, and other West African developers[2]**.**

West Africa's leading share supports the idea that **AI capability formation is not only about research but also about building, sharing, and collaborating through code**.

North Africa's high contribution reflects its strong **technical education systems**, established software engineering communities, and significant activity in open source repositories. Countries like Morocco and Egypt are noted in GitHub growth data as among Africa's largest developer populations[3].
Justification for this strong performance includes:

- Governments investing in digital skills and AI strategies historically more than many regions.
- Large urban tech hubs (e.g., Cairo, Casablanca, Tunis) producing consistent software project contributions on GitHub.
- Proximity to European tech ecosystems encouraging cross-regional coding collaboration.

This suggests that North African developers are not only participating in AI globally, but **actively building code and maintaining GitHub projects at scale**.

[1] GitHub (2024b). *Octoverse: AI leads Python to top language as the number of global developers surges*. [online] The GitHub Blog. Available at: https://github.blog/news-insights/octoverse/octoverse-2024/? [Accessed 24 Feb. 2026].

[2] GitHub (2024a). *GitHub and Microsoft announce GenAI for Youth Program to empower next generation of developers in Africa*. [online] GitHub. Available at: https://github.com/newsroom/press-releases/genai-for-youth-program? [Accessed 24 Feb. 2026].

[3] GitHub (2024b)

East Africa contributes a solid share, led by strong communities in Kenya and increasingly in Ethiopia and Uganda. GitHub reports indicate that East African developers (e.g., Kenya) are among the fastest-growing contributor bases[4].

Rational factors include:

- Government and private sector focus on technology education and coding bootcamps.
- Active open source communities hosting hackathons and training.
- Increasing participation in AI and data science repositories tied to mobile and civic tech innovation.

While not as large as West or North Africa, East Africa's share shows **meaningful code creation capacity**.

Both Central and Southern Africa show relatively smaller shares of GitHub AI activity. This can be interpreted through multiple lenses:

- **Smaller developer populations** overall relative to West and North Africa.
- Lower levels of extensive open source culture or GitHub presence historically.
- Infrastructure and connectivity challenges that may hamper consistent GitHub engagement.

However, smaller does not mean inactive — countries within these regions still host vibrant local ecosystems, though less represented in broad aggregate GitHub counts.

In all, the regional distribution of AI capability building via GitHub in Africa is clearly **concentrated** rather than broad-based. Over **half (53.14%)** of the capability indicators come from West Africa, followed by North Africa's **19.66%**, with other regions trailing behind. The pattern reflects underlying socio-economic and digital infrastructure differences, developer population sizes, and the strength of open source communities. This concentration signals

[4] Itimu, K. (2019). *Kenya Has One of the Fastest Growing Software Developer Communities on GitHub*. [online] Techweez | Tech News, Reviews, Deals, Tips and How To. Available at: https://techweez.com/2019/11/11/kenya-software-developer-communities-github/ [Accessed 24 Feb. 2026].

where AI capability is currently being built most intensively and where supportive policy, infrastructure, and community programming could further accelerate inclusive growth.

7.2. Country-Level distribution of AI capability production in Africa

Figure 22 shows the country-level distribution of AI capability production in Africa. The country-level distribution of AI talent repositories across Africa reveals a highly concentrated landscape in which a small number of countries account for a disproportionate share of total activity.

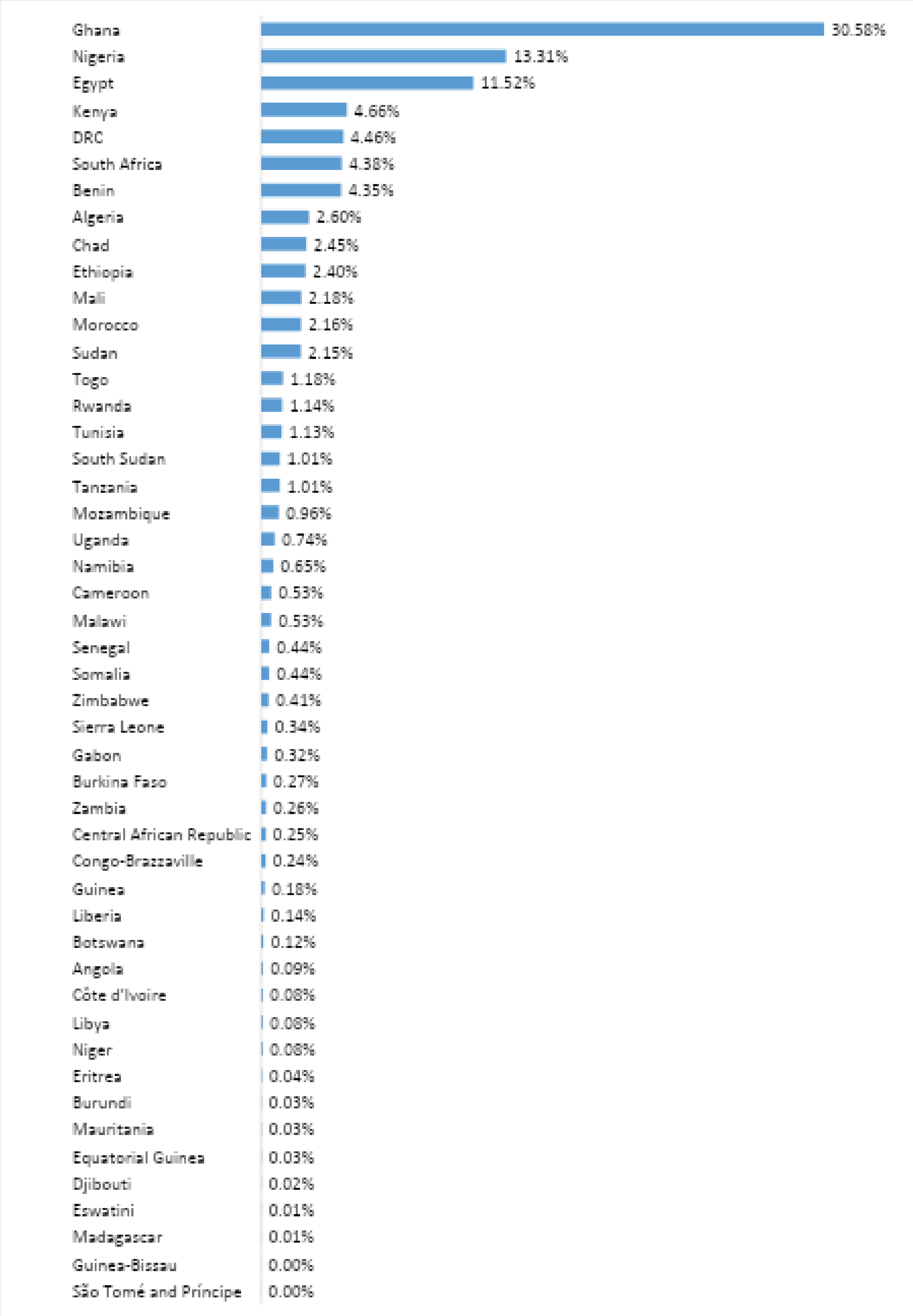


Figure 22: Country-Level distribution of AI capability production in Africa

Out of 27,349 repositories (100%), **Ghana leads decisively with 8,362 repositories, representing 30.58%** of the continental total. This is followed by **Nigeria with 3,639 repositories (13.31%)** and Egypt with 3,151 repositories (11.52%). Together, these three countries account for 55.41% of all AI-related repositories on the continent, demonstrating a strong upper-tier concentration of AI capability formation.

Ghana's leading position at 30.58% is particularly notable, as it alone contributes nearly one-third of Africa's AI talent repositories. This dominance suggests an exceptionally active open-source culture and strong participation in AI-related development communities. Its performance may reflect sustained investments in digital entrepreneurship ecosystems, coding education, and internationally connected technology hubs.

Nigeria, with 13.31%, reinforces West Africa's broader regional dominance in AI capability building. Given Nigeria's large developer population and expanding technology sector, its substantial contribution is consistent with patterns observed in broader African software development growth. Egypt, contributing 11.52%, represents North Africa's strongest national performer and underscores the importance of established engineering education systems and integration with global technology networks.

A second tier of contributors includes Kenya (4.66%), Democratic Republic of the Congo (4.46%), South Africa (4.38%), and Benin (4.35%). Each of these countries contributes between four and five percent of total repositories. While individually far behind the top three, collectively this second tier represents a meaningful layer of distributed AI activity. Kenya's position reflects East Africa's growing innovation ecosystem, particularly in data science and civic technology. South Africa's contribution aligns with its historically strong higher education institutions and established software engineering base. The Democratic Republic of the Congo and Benin's presence at comparable levels suggests that AI repository production is not limited solely to traditionally dominant African technology economies, but is also emerging in less globally recognized ecosystems.

A middle tier of countries—including Algeria (2.60%), Chad (2.45%), Ethiopia (2.40%), Mali (2.18%), Morocco (2.16%), and Sudan (2.15%)—each contribute between two and three percent of total repositories. While individually modest, their combined contribution strengthens the argument that AI capability is spreading beyond the primary leaders. Nevertheless, none of these countries individually approaches the scale of Ghana, Nigeria, or Egypt, reinforcing the steep drop-off after the top three.

Beyond this group, the distribution becomes increasingly fragmented. Countries such as Rwanda (1.14%), Tunisia (1.13%), Tanzania (1.01%), Uganda (0.74%), Cameroon (0.53%), Senegal (0.44%), and Zimbabwe (0.41%) contribute relatively small shares individually. At the lower end of the distribution, several countries account for less than 0.10% each, including Angola, Libya, Niger, Eritrea, Burundi, Madagascar, and São Tomé and Príncipe. This long tail indicates that while AI repository activity exists across nearly the entire continent, intensity varies dramatically.

Statistically, the concentration pattern is clear. The top three countries contribute 55.41% of total repositories, the top seven exceed 70%, and the majority of remaining countries individually contribute less than 1%. This distribution reflects a classic concentration curve, where AI capability formation is clustered in a few leading national ecosystems while the remainder of the continent participates at comparatively lower scales. The evidence therefore supports the conclusion that AI talent repository production in Africa is highly concentrated at the country level, with leadership anchored primarily in Ghana, Nigeria, and Egypt, followed by a secondary layer of mid-sized contributors and a broad but thinly distributed long tail of emerging ecosystems.

7.3 Distribution of AI Capability Production in Africa by Skill clusters

Figure 23 presents the AI Talent Repositories by Skill Cluster. The distribution of AI talent repositories across skill clusters reveals a sharply skewed structure in which a small number of capability domains dominate African developer activity.

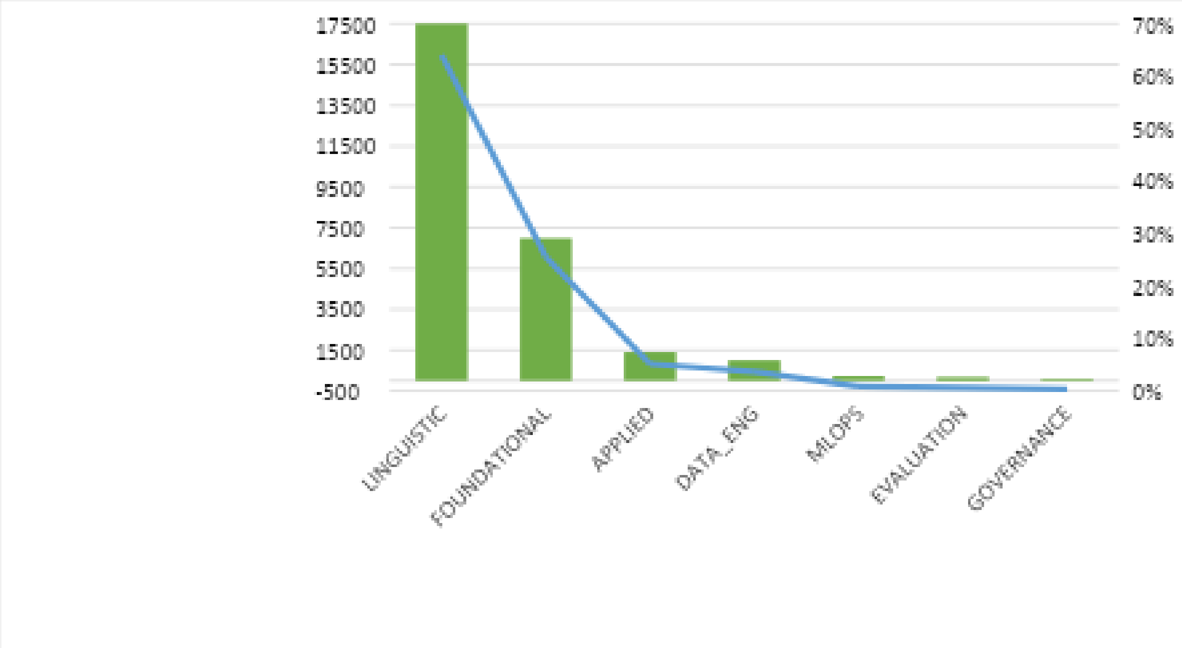


Figure 23: AI Talent Repositories by Skill Cluster

Out of 27,349 total repositories (100%), the **Linguistic cluster accounts for 17,498 repositories (63.98%)**, followed by **Foundational AI skills with 6,977 repositories (25.51%)**. All other clusters collectively represent less than 11% of activity. This distribution demonstrates a clear hierarchy in African AI capability formation, with language-centered AI development occupying the overwhelming majority of observable open-source contributions.

The dominance of the Linguistic cluster at 63.98% suggests that African developers are primarily engaging with natural language processing (NLP), conversational AI, text analytics, translation systems, and generative AI applications. This pattern is highly consistent with Africa's linguistic diversity and communication needs. The continent hosts over 2,000 languages, and many remain underrepresented in global AI systems. As a result, developers are strongly incentivized to build language datasets, fine-tune models, develop chatbots, and create localized AI applications. The global explosion of large language models (LLMs) since 2022 has further lowered entry barriers, enabling developers to fine-tune or integrate existing models rather than train computationally expensive systems from scratch. **The evidence therefore indicates that African AI activity is heavily oriented toward language adaptation, localization, and application-layer innovation rather than deep infrastructure development.**

The Foundational cluster, representing 25.51% of repositories, forms the second major pillar of activity. This cluster includes core machine learning algorithms, model architectures, experimentation frameworks, and mathematical implementations. While substantially smaller than Linguistic activity, one-quarter of all repositories falling into this category suggests that a meaningful segment of developers is engaging with core AI model construction and experimentation. However, the gap between Linguistic (63.98%) and Foundational (25.51%) indicates that **model usage and adaptation significantly outweigh original model-building at scale**. This imbalance may reflect computational constraints, limited access to large-scale training infrastructure, and the high capital requirements associated with frontier model development.

Applied AI accounts for 1,402 repositories (5.13%), representing domain-specific solutions such as health-tech AI, fintech analytics, agriculture optimization tools, and computer vision use cases. The modest size of this cluster suggests that although AI is being deployed to solve sectoral problems, applied innovation remains secondary to language-focused experimentation. This may be due to the complexity of integrating AI into regulated sectors, limited access to structured datasets in certain industries, or the higher barriers associated with commercialization and enterprise integration. Nonetheless, the presence of over five percent of repositories in this cluster indicates an emerging but not yet dominant layer of sectoral AI deployment.

Though, a major theme from the interviews concerns the position of African AI development within the global technology stack. The interview data suggests that most AI activity on the continent currently occurs at the **application layer rather than the foundational model layer**. One of the participants emphasises (00:05:45) that *"all of us in Africa are playing in the application layer… we build applications using the foundational layer through APIs from the big players or implementing open-source models."* This indicates that African developers primarily leverage existing global models—such as large language models or open-source architectures—rather than developing proprietary foundational models.

The participant explains that this pattern is largely driven by **economic realities**, particularly the substantial financial investment required to build and train foundational AI systems. According to the discussion (00:06:15), *"building a foundational model is also a good* *approach, but it needs a lot of investment that doesn't exist."* Without sufficient capital and computing infrastructure, African developers instead focus on **building locally relevant AI applications that integrate with existing enterprise systems and legacy technologies**. This strategic focus on applications allows African innovators to create value despite structural limitations in the global AI ecosystem. Ultimately, the discussion highlights that **application-driven innovation may represent a pragmatic pathway for African AI development in the near term**.

Data Engineering contributes 998 repositories (3.65%), highlighting that a smaller but essential group of developers is focused on pipelines, data cleaning, feature engineering, and storage architectures. The relatively low percentage suggests that **data infrastructure development is not yet proportionate to model experimentation activity**, which could present long-term scalability constraints. Strong AI ecosystems typically require robust data engineering backbones; the comparatively modest size of this cluster may reflect limited enterprise-scale AI deployment environments across parts of the continent.

MLOps, at 223 repositories (0.82%), and Evaluation, at 172 repositories (0.63%), represent highly specialized layers of AI system maturity. MLOps involves deployment automation, monitoring systems, CI/CD pipelines for models, and production lifecycle management. Evaluation includes benchmarking, bias testing, robustness checks, and model performance auditing. The fact that both clusters fall below one percent indicates that **production-grade AI system management and formal evaluation infrastructures are still nascent within African open-source ecosystems**. These domains typically expand when AI transitions from experimentation to large-scale enterprise deployment, suggesting that most current activity remains in exploratory or prototype stages.

Governance, comprising only 79 repositories (0.29%), is the smallest cluster. This includes work on AI ethics frameworks, regulatory tools, bias auditing systems, and compliance architectures. The minimal share suggests that regulatory engineering and AI policy tooling are not yet primary areas of developer focus. This does not imply absence of governance discourse, but rather indicates that open-source technical implementations of governance mechanisms remain limited. In many ecosystems globally, governance tooling tends to follow technological scaling rather than precede it, which may explain its comparatively low representation.

Overall, the statistical distribution reveals a **highly concentrated AI skill structure**, with nearly two-thirds of all activity centered on Linguistic AI and over one-quarter on Foundational skills. Together, these two clusters account for 89.49% of all repositories. The remaining five clusters collectively represent just 10.51%, indicating limited emphasis on deployment engineering, lifecycle management, evaluation rigor, and governance tooling. The findings therefore suggest that African AI developer activity is currently **application-layer heavy, language-focused, and experimentation-driven**, with comparatively limited engagement in large-scale infrastructure, operationalization, and regulatory engineering. This pattern is consistent with ecosystems in earlier or rapidly expanding phases of AI capability development, where accessibility and immediate use cases drive participation more strongly than deep infrastructural or governance investments.

7.4 Sub-Regional Leadership in AI Capability Production Across AI Skill Clusters

Figure 24 summarises the AI Talent Repositories by Sub-Region in each Skill Cluster. The sub-regional distribution of AI repositories across skill clusters reveals a **consistent structural pattern of West African dominance**, with important variations in North Africa and selective specialization in Southern and East Africa. Examining each cluster individually provides a clearer understanding of where specific AI capabilities are being built and why these geographies are emerging as leaders.

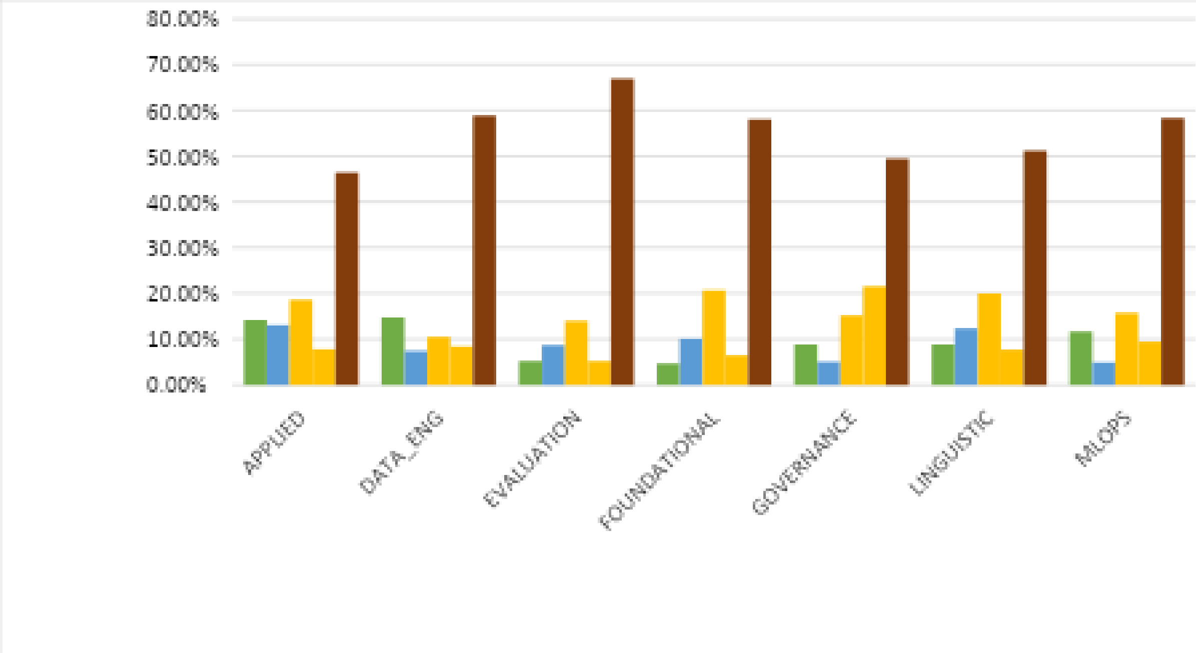


Figure 24: AI Talent Repositories by Sub-Region in each Skill Cluster

In the Applied cluster (1,402 repositories), **West Africa leads decisively with 651 repositories (46.43%)**, followed by North Africa (18.62%), Central Africa (14.12%), East Africa (13.05%), and Southern Africa (7.77%). The strong West African performance reflects the region's rapidly expanding startup ecosystem, particularly in Nigeria and Ghana, where AI is being deployed in fintech, health-tech, logistics, and e-commerce solutions. Cities such as Lagos and Accra have become major innovation hubs, supported by venture funding inflows and accelerator programs. The applied orientation aligns with the region's entrepreneurial ecosystem, which emphasizes solving immediate market problems rather than purely academic experimentation. North Africa's second position likely reflects structured sectoral adoption of AI in areas such as smart agriculture, language services, and public sector modernization initiatives, particularly in Egypt and Morocco.

In Data Engineering (998 repositories), **West Africa again dominates with 588 repositories (58.92%)**, more than five times the contribution of North Africa (10.52%) and significantly ahead of Central (14.73%), Southern (8.42%), and East Africa (7.41%). This strong concentration suggests that West African ecosystems are not only building applications but also increasingly constructing data pipelines and infrastructure to support them. Nigeria's rapidly growing developer population and enterprise digitalization drive likely contribute to this emphasis. The comparatively smaller shares in East and Southern Africa may reflect more mature but narrower enterprise AI deployment bases, while North Africa's moderate participation aligns with its institutional and telecom-driven digital infrastructure investments.

The Evaluation cluster (172 repositories) shows the most extreme concentration. **West Africa accounts for 115 repositories (66.86%)**, followed by North Africa (13.95%), East Africa (8.72%), and both Central and Southern Africa at 5.23% each. Evaluation work—such as benchmarking, bias detection, and performance validation—often grows in ecosystems where AI experimentation has already scaled. The dominance of West Africa here mirrors its overwhelming presence in Linguistic and Foundational repositories, suggesting that once experimentation expands, evaluation practices follow. The limited activity in other regions likely reflects the early developmental stage of structured AI auditing and benchmarking practices across much of the continent.

In Foundational AI (6,977 repositories), which includes core machine learning architectures and algorithmic experimentation, **West Africa leads with 4,053 repositories (58.09%)**, while North Africa follows with 1,444 (20.70%). East Africa contributes 10.10%, Southern Africa 6.45%, and Central Africa 4.66%. This distribution highlights two major centers of technical depth: West and North Africa. North Africa's strong second-place position is particularly notable and can be linked to historically strong engineering institutions and government-backed AI strategies in countries such as Egypt and Morocco. Meanwhile, West Africa's lead reflects scale—its developer population growth has been among the fastest globally in recent GitHub reporting. The data suggest that while West Africa leads in volume, North Africa maintains significant technical core capacity in model-centric AI work.

Governance (79 repositories) is the smallest cluster, but it presents a slightly different pattern. **West Africa still leads with 49.37%**, yet Southern Africa records a relatively strong share at 21.52%, surpassing North Africa (15.19%), Central Africa (8.86%), and East Africa (5.06%). Southern Africa's comparatively higher governance share may reflect South Africa's established legal, regulatory, and academic research institutions, which have historically engaged in technology ethics and digital rights discourse. Governance tooling often emerges from policy-mature environments, and Southern Africa's relative institutional depth likely explains its disproportionate presence in this otherwise small cluster.

In the Linguistic cluster (17,498 repositories), which represents the largest skill domain overall, **West Africa leads with 8,956 repositories (51.18%)**, followed by North Africa (19.99%), East Africa (12.30%), Central Africa (8.87%), and Southern Africa (7.66%). This distribution reflects demographic and linguistic realities. West Africa contains some of the continent's most populous countries and is characterized by high levels of multilingualism, creating strong incentives for natural language processing, translation systems, and chatbot development. The rapid adoption of generative AI technologies has likely accelerated this pattern. North Africa's strong participation is consistent with Arabic-language AI development and integration with Middle Eastern and European research networks.

In MLOps (223 repositories), **West Africa again leads with 58.30%**, followed by North Africa (15.70%), Central Africa (11.66%), Southern Africa (9.42%), and East Africa (4.93%). MLOps requires operational maturity and enterprise-scale AI deployment. West Africa's leadership here suggests that portions of its ecosystem are transitioning from experimentation toward production environments. North Africa's second-place share aligns with structured enterprise adoption patterns, particularly in telecom and public sector digital transformation initiatives.

Thus, across all seven skill clusters, **West Africa leads in every category by a substantial margin**, often exceeding 50% of total repositories. This indicates that the region is currently the primary engine of AI capability formation on the continent. North Africa consistently occupies second position in technically intensive clusters such as Foundational AI and MLOps, reflecting institutional depth and engineering traditions. Southern Africa demonstrates relative specialization in Governance, suggesting regulatory and academic maturity, while East and Central Africa contribute meaningfully but at lower aggregate volumes.

The cross-cluster pattern reveals that African AI capability is geographically concentrated but not monolithic. Different regions display varying comparative strengths shaped by developer population scale, institutional maturity, entrepreneurial ecosystems, regulatory traditions, and digital infrastructure investments. The data therefore support the conclusion that **AI skill development in Africa is regionally stratified, with West Africa functioning as the**

dominant growth hub and North Africa serving as a secondary technical anchor across multiple advanced clusters.

7.5 Country Leadership in AI Capability Production Across AI Skill Clusters

A country-level disaggregation of AI talent repositories reveals **clear national champions within each skill cluster**, alongside structural patterns that reflect differences in ecosystem maturity, developer population scale, higher education capacity, and startup ecosystem depth. Across nearly all clusters, three countries—Ghana, Nigeria, and Egypt—consistently dominate. However, the degree and nature of dominance vary by technical domain. Figure 25 displays the AI Talent Repositories by Skill Cluster and Country.

country	APPLIED	DATA_ENG	EVALUATION	FOUNDATIONAL	GOVERNANCE	LINGUISTIC	MLOPS
Algeria	1.93%	2.20%	3.49%	3.87%	3.80%	2.14%	3.59%
Angola	0.21%	0.10%	0.00%	0.19%	0.00%	0.05%	0.00%
Benin	4.14%	3.31%	2.33%	3.43%	3.80%	4.81%	4.93%
Botswana	0.14%	0.00%	0.00%	0.10%	0.00%	0.14%	0.00%
Burkina Faso	0.36%	0.20%	0.00%	0.24%	0.00%	0.29%	0.00%
Burundi	0.00%	0.20%	0.00%	0.01%	0.00%	0.02%	0.45%
Cameroon	0.57%	0.30%	0.00%	0.30%	2.53%	0.64%	0.00%
Central African Republic	0.29%	0.20%	0.00%	0.10%	0.00%	0.32%	0.00%
Chad	5.35%	0.60%	1.74%	1.38%	2.53%	2.76%	1.79%
Congo-Brazzaville	0.29%	1.20%	0.58%	0.20%	0.00%	0.19%	0.45%
Côte d'Ivoire	0.07%	0.20%	0.00%	0.07%	0.00%	0.09%	0.00%
Djibouti	0.00%	0.00%	0.00%	0.01%	0.00%	0.02%	0.00%
DRC	7.28%	12.22%	2.33%	2.44%	1.27%	4.57%	9.42%
Egypt	8.63%	2.20%	7.56%	11.90%	7.59%	12.26%	5.83%
Equatorial Guinea	0.00%	0.00%	0.00%	0.01%	0.00%	0.03%	0.00%
Eritrea	0.00%	0.10%	0.00%	0.01%	0.00%	0.06%	0.00%
Eswatini	0.00%	0.00%	0.00%	0.04%	0.00%	0.01%	0.00%
Ethiopia	1.64%	1.80%	1.16%	1.99%	1.27%	2.70%	0.90%
Gabon	0.36%	0.20%	0.58%	0.23%	2.53%	0.35%	0.00%
Ghana	22.33%	34.07%	40.70%	33.70%	26.58%	29.60%	39.01%
Guinea	0.14%	0.30%	0.00%	0.11%	0.00%	0.21%	0.45%
Guinea-Bissau	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%
Kenya	5.78%	3.51%	5.23%	3.96%	2.53%	4.97%	1.35%
Liberia	0.43%	0.10%	0.58%	0.04%	0.00%	0.16%	0.00%
Libya	0.07%	0.00%	0.00%	0.01%	0.00%	0.11%	0.45%
Madagascar	0.00%	0.00%	0.00%	0.01%	0.00%	0.01%	0.00%
Malawi	0.36%	0.10%	0.58%	0.56%	0.00%	0.56%	0.45%
Mali	1.36%	1.90%	1.74%	2.77%	0.00%	2.06%	0.45%
Mauritania	0.00%	0.00%	0.00%	0.04%	0.00%	0.03%	0.00%
Morocco	3.78%	3.81%	0.58%	2.06%	3.80%	1.98%	2.24%
Mozambique	0.86%	0.40%	0.00%	0.33%	1.27%	1.27%	0.00%

country	APPLIED	DATA_ENG	EVALUATION	FOUNDATIONAL	GOVERNANCE	LINGUISTIC	MLOPS
Namibia	1.28%	0.20%	0.00%	0.37%	0.00%	0.76%	0.00%
Niger	0.21%	0.00%	0.00%	0.16%	0.00%	0.04%	0.45%
Nigeria	15.19%	16.93%	19.77%	15.81%	18.99%	11.90%	9.87%
Rwanda	2.07%	0.20%	0.00%	0.95%	1.27%	1.22%	0.45%
São Tomé and Príncipe	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%
Senegal	0.14%	0.30%	0.00%	0.43%	0.00%	0.47%	1.35%
Sierra Leone	0.93%	0.30%	0.58%	0.21%	0.00%	0.34%	0.90%
Somalia	0.43%	0.10%	0.00%	0.24%	0.00%	0.54%	0.00%
South Africa	4.21%	7.11%	4.07%	4.27%	18.99%	4.15%	8.97%
South Sudan	1.78%	1.10%	0.58%	0.96%	0.00%	0.98%	0.45%
Sudan	3.28%	1.30%	1.16%	1.69%	0.00%	2.30%	2.69%
Tanzania	0.71%	0.40%	0.58%	1.26%	0.00%	0.99%	0.45%
Togo	1.14%	1.30%	1.16%	1.12%	0.00%	1.21%	0.90%
Tunisia	0.93%	1.00%	1.16%	1.12%	0.00%	1.16%	0.90%
Uganda	0.64%	0.00%	1.16%	0.70%	0.00%	0.80%	0.90%
Zambia	0.21%	0.00%	0.00%	0.23%	1.27%	0.30%	0.00%
Zimbabwe	0.50%	0.50%	0.58%	0.34%	0.00%	0.42%	0.00%
%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Total (N)	1402	998	172	6977	79	17498	223

Figure 25: AI Talent Repositories by Skill Cluster and Country

In the Applied cluster (1,402 repositories), **Ghana leads with 313 repositories (22.33%)**, followed by Nigeria (15.19%) and Egypt (8.63%). The Democratic Republic of the Congo (7.28%) and Kenya (5.78%) form a secondary tier. Ghana's strong position aligns with the rapid expansion of its innovation ecosystem, particularly in Accra, where AI-driven startups operate in fintech, agritech, and health innovation. The country has benefited from international AI research collaborations and strong coding bootcamp penetration.

Nigeria's position reflects its role as Africa's largest startup market by venture funding volume, with applied AI widely used in financial services, logistics, and digital commerce. Egypt's performance corresponds with structured state-led digital transformation strategies and expanding smart city initiatives. **The evidence suggests that applied AI leadership correlates strongly with entrepreneurial ecosystem vibrancy and startup capital flows.**

In Data Engineering (998 repositories), **Ghana again leads decisively with 34.07%**, followed by Nigeria (16.93%) and the Democratic Republic of the Congo (12.22%). South Africa (7.11%) and Morocco (3.81%) follow. Data engineering capacity often develops where application ecosystems mature and require scalable pipelines. Ghana's leadership here reinforces the interpretation that its AI ecosystem is not merely experimental but increasingly infrastructural.

Nigeria's strong showing reflects the scale of enterprise digitization across its banking and telecom sectors. South Africa's presence is consistent with its comparatively advanced enterprise IT systems and longstanding corporate data infrastructure environment.

In Evaluation (172 repositories), **Ghana accounts for an extraordinary 40.70%**, followed by Nigeria (19.77%) and Egypt (7.56%). Kenya (5.23%) and South Africa (4.07%) contribute modestly. Evaluation work—benchmarking, bias testing, and validation—typically expands once experimentation scales. Ghana's dominance suggests a relatively mature internal experimentation culture requiring performance validation and benchmarking.

Nigeria's strong share indicates growing attention to robustness and quality assurance within its expanding AI projects. Egypt's presence reflects institutional research traditions tied to universities and engineering faculties. **The concentration of evaluation activity in a few countries indicates that systematic model auditing remains geographically narrow across the continent.**

The Foundational cluster (6,977 repositories) shows **Ghana leading with 33.70%**, followed by Nigeria (15.81%) and Egypt (11.90%). Benin (3.43%), Kenya (3.96%), and South Africa (4.27%) contribute meaningful but smaller shares. Foundational AI includes core algorithm development and machine learning experimentation. Ghana's dominance suggests a substantial base of technically oriented contributors beyond surface-level application integration.

Nigeria's large developer population supports broad experimentation, while Egypt's strong engineering education system explains its sustained foundational presence. Egypt's universities have historically produced large numbers of engineering graduates, and government-backed AI strategies have emphasized research infrastructure, helping explain its relatively high share in core AI model development.

Governance (79 repositories) is highly concentrated in a few countries. **Ghana leads with 26.58%**, followed by Nigeria (18.99%) and South Africa (18.99%), with Egypt contributing 7.59%. South Africa's strong relative share is notable; it reflects the country's well-developed legal institutions, academic research communities, and digital rights discourse. Governance tooling often emerges in environments with established regulatory traditions and civil society engagement. Ghana and Nigeria's leadership suggests that ethical AI discussions are beginning to translate into technical implementations within their developer ecosystems. However, the small absolute size of this cluster confirms that governance engineering remains underdeveloped continent-wide.

The Linguistic cluster (17,498 repositories) represents the largest skill domain, and **Ghana again leads with 29.60%**, followed by Egypt (12.26%) and Nigeria (11.90%). Kenya (4.97%), Benin (4.81%), and the Democratic Republic of the Congo (4.57%) form a second tier. Linguistic dominance aligns closely with Africa's multilingual context and the global rise of large language models.

Ghana's leadership may reflect active participation in NLP-focused initiatives and dataset creation for local languages. Egypt's strong position is consistent with Arabic-language AI development, supported by regional demand across North Africa and the Middle East. Nigeria's large population and linguistic diversity similarly create incentives for chatbot development, translation systems, and localized generative AI applications. **This distribution underscores that language-focused AI is the primary entry point into advanced AI ecosystems across Africa.**

In MLOps (223 repositories), **Ghana leads with 39.01%**, followed by Nigeria (9.87%), South Africa (8.97%), and the Democratic Republic of the Congo (9.42%), with Egypt contributing 5.83%. MLOps reflects deployment maturity—continuous integration pipelines, monitoring systems, and production lifecycle management. Ghana's dominance suggests that portions of its ecosystem are transitioning from experimentation to operational deployment. South Africa's presence aligns with enterprise-scale AI implementation within financial services and corporate sectors. Nigeria's share reflects its expanding startup and fintech environments, where production-grade AI systems are increasingly necessary.

Across all seven skill clusters, **Ghana emerges as the single most dominant national contributor**, leading in every category and often by wide margins. Nigeria and Egypt consistently occupy second- and third-tier leadership positions, forming a triad that anchors African AI capability development. South Africa demonstrates particular relative strength in governance and enterprise-oriented clusters, while countries such as Kenya, Benin, and the Democratic Republic of the Congo contribute meaningfully in applied and linguistic domains.

The data reveal a **highly concentrated national structure**, where a small number of countries account for the majority of AI repository production across technical layers—from foundational algorithms to deployment and evaluation. This pattern suggests that AI capability in Africa is not evenly distributed but clustered in ecosystems with strong developer growth, supportive policy environments, expanding start-up capital, and institutional educational depth.

7.6 Annual distribution of AI Talent Production in Africa

Figure 26 presents the annual distribution of AI Talent Repositories in Africa. The temporal distribution of AI talent repositories from 2009 to 2026 shows a **clear and sustained maturation pattern**, particularly after 2016, with an accelerated surge between 2023 and 2025.

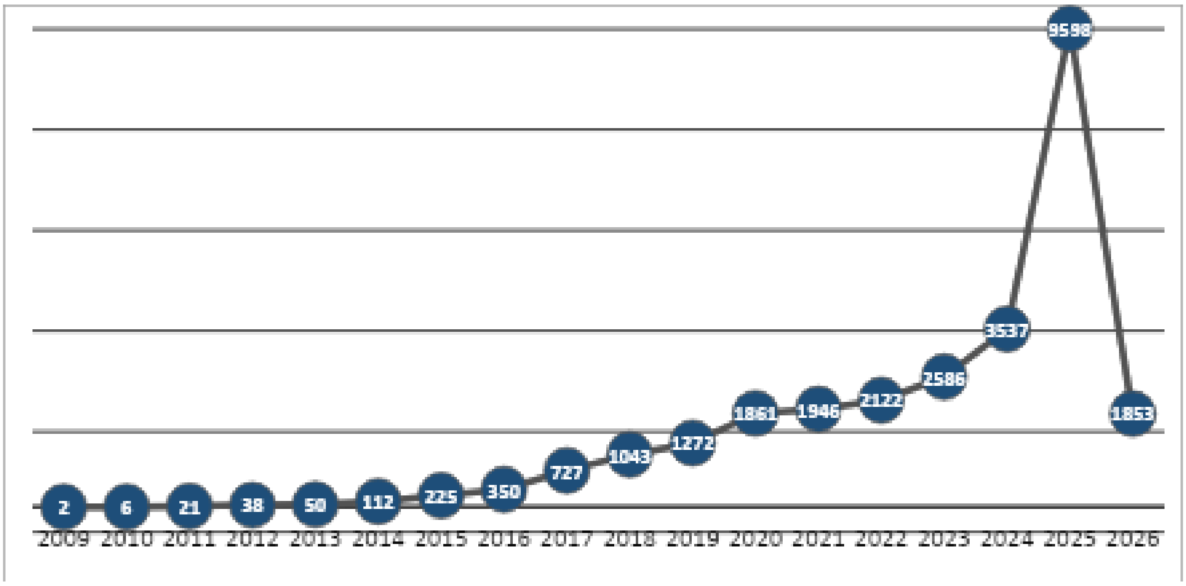


Figure 26: Annual distribution of AI Talent Repositories in Africa

The trajectory moves from very low activity in the early years (2 repositories in 2009 and single-digit growth through 2010–2012) to steady expansion from 2013 onward, followed by exponential growth in recent years. This indicates that African AI communities have transitioned from an emerging phase to a rapid scaling phase, especially in the last five years.

Between 2009 and 2016, growth was gradual but consistent, rising from 2 repositories in 2009 to 350 in 2016. This period likely reflects foundational digital infrastructure expansion across the continent, including improved internet penetration, increased access to cloud computing, the rise of global developer platforms such as GitHub, and the growth of computer science education programs. During this phase, AI activity appears exploratory and niche, with communities building early capability and engaging primarily in experimentation rather than large-scale production.

The period from 2017 to 2022 marks a structural acceleration, with repositories increasing from 727 in 2017 to 2,122 in 2022. This phase aligns globally with the deep learning revolution and the widespread adoption of open-source machine learning frameworks such as TensorFlow and PyTorch. The democratization of AI tooling reduced barriers to entry, enabling developers across Africa to participate in model development without requiring large institutional resources. At the same time, venture capital growth in African technology ecosystems—particularly in West and North Africa—expanded startup-driven AI experimentation. Increased participation in global hackathons, online AI courses, and remote collaboration further strengthened community engagement. This period reflects **community consolidation and capability scaling**.

The most dramatic shift occurs in 2023–2025, where repositories surge from 2,586 in 2023 to 3,537 in 2024 and then to 9,598 in 2025. This represents an exponential increase. This acceleration strongly coincides with the global rise of generative AI and large language models, particularly after the public release of advanced conversational AI systems in late 2022. The accessibility of pre-trained models significantly lowered technical entry barriers, enabling developers to create, fine-tune, and adapt AI systems without training models from scratch. Given that earlier analyses showed that over 63% of African repositories are linguistic, this temporal spike likely reflects the widespread adoption of language model-based development, chatbot creation, and AI-assisted coding workflows.

Additionally, the growth in repositories may also be influenced by increased digital entrepreneurship across countries such as Ghana, Nigeria, and Egypt, which were identified as leading contributors in both research and capability datasets. Expanding tech hubs, accelerator programs, remote work integration, and youth participation in global developer ecosystems likely contributed to the observed expansion. The proliferation of online AI education platforms during this period also reduced skill acquisition barriers.

The slight decline in 2026 (1,853 repositories) compared to 2025 does not necessarily indicate contraction. Instead, it may reflect a partial-year reporting effect or data capture timing. Given the long-term upward trajectory, the broader pattern still indicates strong structural growth.

Overall, the evidence shows that African AI communities are **clearly maturing over time**, transitioning from minimal activity in the early 2010s to exponential open-source production in the mid-2020s. The trigger behind this behaviour appears to be a combination of global technological shifts (deep learning expansion and generative AI), improved digital infrastructure, increased access to cloud-based tools, rising startup ecosystems, expanded AI education, and lower barriers to participation in open-source development. The pattern reflects not only growth in volume but also ecosystem deepening, particularly in linguistic AI development and foundational model experimentation.

7.7 Annual AI Talent Repositories across Africa Sub-regions

Figure 27 visualises the annual AI Talent Repositories across Africa Sub-regions (2009-2026). There are **clear and structurally meaningful trend changes in regional shares over time**, and the patterns indicate both long-term concentration dynamics and gradual diversification within Africa's AI talent repository ecosystem.

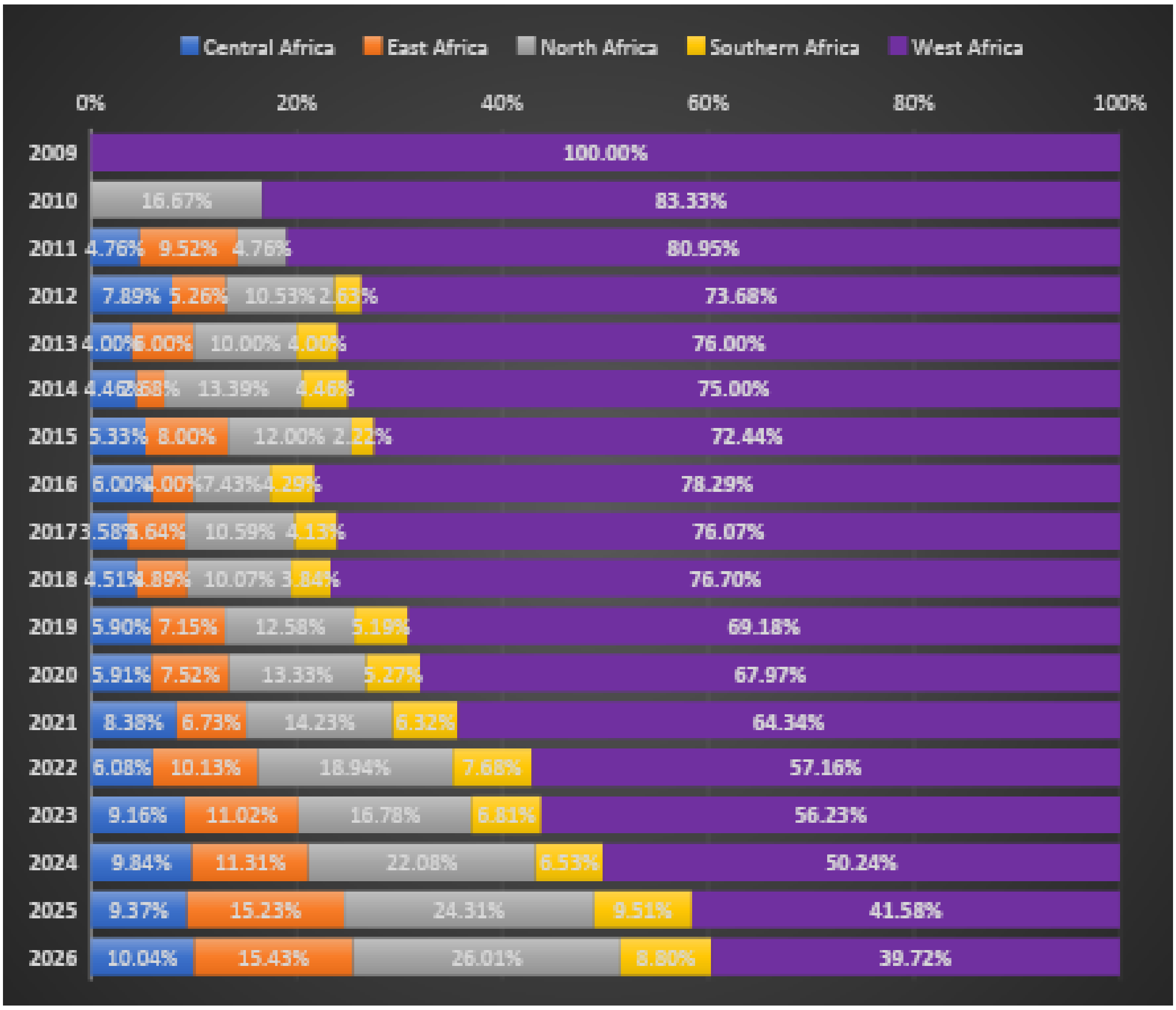


Figure 27: Annual AI Talent Repositories across Africa Sub-regions (2009-2026)

From 2009 through approximately 2018, **West Africa dominates overwhelmingly**, consistently accounting for around **70–80% of annual repositories**. For example, West Africa represents 100% in 2009 (with only two total repositories), and remains above 75% in most early years. This indicates that the initial phase of AI open-source activity on the continent was highly centralized geographically. During this period, other regions—particularly Central, East, and Southern Africa—contributed only marginal shares. This reflects the early maturity stage of ecosystem development, where AI participation was concentrated in a limited number of digitally active countries, most notably in West Africa.

Starting around 2019–2021, we observe the beginning of a structural shift. West Africa's share begins to decline gradually—from about **69% in 2019 to 67.97% in 2020 and 64.34% in 2021**—while North and East Africa start increasing their proportional contributions. This shift suggests that AI participation was spreading beyond the initial core hubs. It corresponds with the broader expansion of developer education, increased cloud accessibility, and greater continental engagement with open-source AI frameworks.

The most significant transformation occurs between 2022 and 2025. During this period, West Africa's share declines sharply from **57.16% in 2022 to 56.23% in 2023, then to 50.24% in 2024, and finally to 41.58% in 2025**. While West Africa remains the largest contributor, its dominance is substantially reduced. At the same time, North Africa's share increases steadily—from **18.94% in 2022 to 16.78% in 2023, 22.08% in 2024, and 24.31% in 2025**. East Africa also grows significantly, rising from **10.13% in 2022 to 15.23% in 2025**. Central Africa shows gradual improvement as well, increasing from about 6–7% earlier to approximately **10% by 2026**. Southern Africa remains relatively stable but does not experience comparable acceleration.

These shifts indicate a **pattern of regional diversification**, even though West Africa remains dominant in absolute numbers. In other words, while total repository growth has accelerated dramatically, particularly after 2023, the growth is increasingly distributed across multiple regions rather than being concentrated solely in West Africa. This suggests ecosystem maturation, where additional regions are beginning to participate more actively in AI capability building.

The sharp surge in total repositories in 2025 (9,598) also plays a role in reshaping regional shares. Because growth during this period was rapid across multiple regions, proportional contributions shifted even if absolute numbers increased everywhere. North Africa's strong expansion in 2024–2025 is particularly notable and may reflect intensified engagement with generative AI tools, stronger institutional adoption, and expanded developer participation in countries such as Egypt and Morocco. East Africa's rising share similarly suggests deepening developer ecosystems in Kenya and neighboring countries.

Importantly, although West Africa's share declines in percentage terms, its absolute numbers continue to rise significantly. Therefore, the pattern does not indicate decline in West Africa; rather, it reflects **relative regional convergence** as other regions accelerate faster in recent years.

In summary, there are clear trend changes in regional shares over time. The ecosystem moved from extreme West African concentration in the early years toward a more diversified structure in the mid-2020s. West Africa remains the leading hub, but North and East Africa are steadily increasing their relative contributions. This indicates **gradual geographic diffusion of AI capability production across the continent**, even within a rapidly expanding overall market.

7.8 Annual AI Talent Production across Skill Clusters

Figure 28 presents the Annual AI Talent Repositories across Skill Clusters (2009-2026). The data clearly show significant year-on-year trend shifts in cluster shares, indicating structural evolution in Africa's AI talent repository ecosystem between 2009 and 2026. The patterns reveal both long-term dominance stability and recent diversification across technical domains.

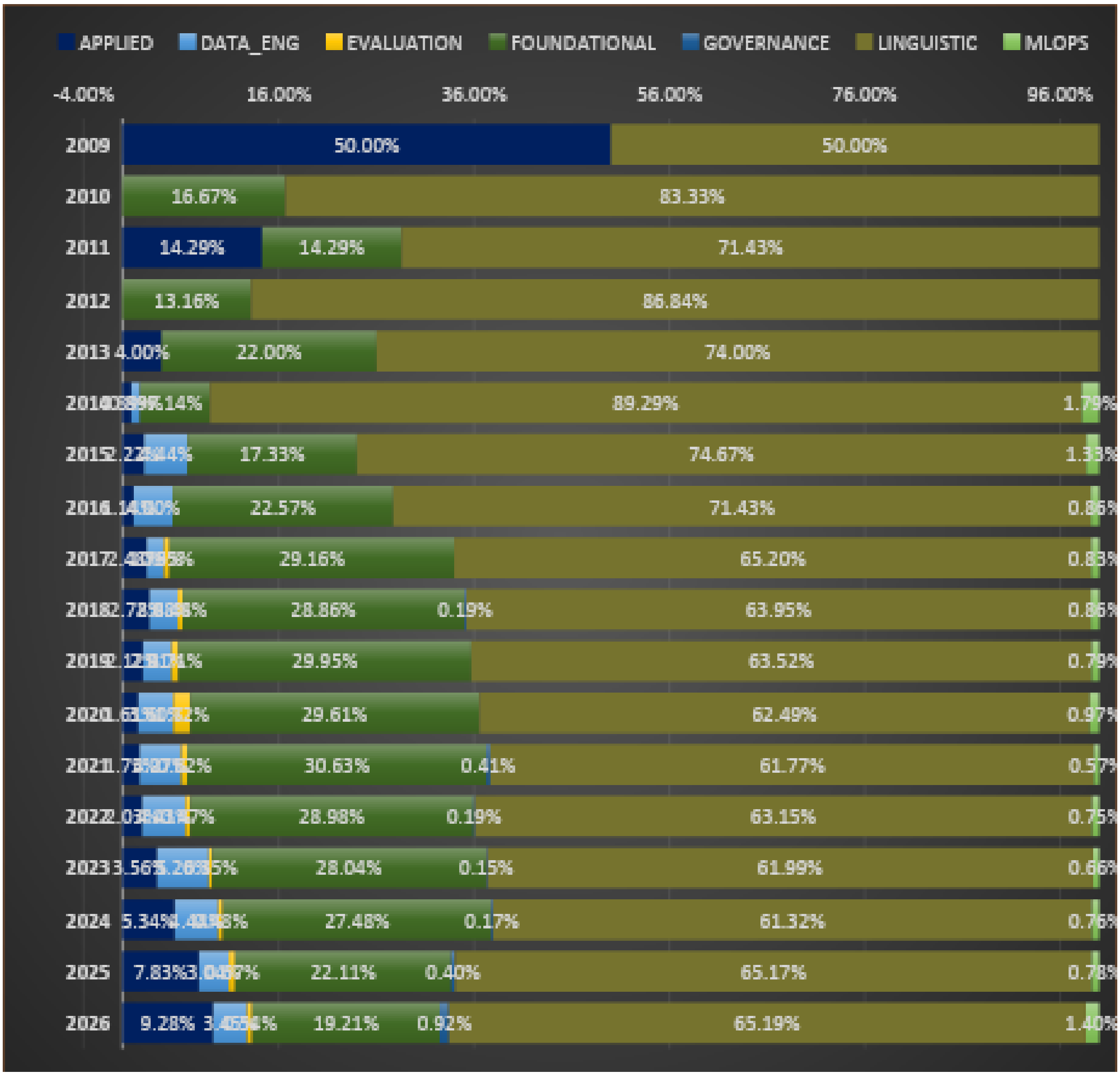


Figure 28: Annual AI Talent Repositories across Skill Clusters (2009-2026)

From 2009 through approximately 2016, the ecosystem was overwhelmingly dominated by the **Linguistic cluster**, which consistently accounted for between **71% and 89% of annual repositories**. For example, linguistic activity represented **83.33% in 2010**, **86.84% in 2012**, and **89.29% in 2014**. During this early phase, other clusters such as Foundational, Applied, Data Engineering, Governance, and MLOps contributed only marginal shares. This pattern reflects an ecosystem in its initial expansion stage, where developers were primarily experimenting with language-based applications, likely due to the lower computational barriers and the accessibility of text-based AI tools.

Beginning around 2017, a structural shift becomes visible. While Linguistic AI remains dominant, its share gradually declines from the mid-70% range to approximately **61–63% between 2017 and 2024**, and stabilizes around **65% in 2025–2026**. Although still the largest category by a wide margin, this slight reduction indicates gradual diversification of AI activity across other clusters.

The most notable upward trend occurs in the **Foundational cluster**. Foundational repositories increased steadily in absolute terms and maintained a substantial share, typically ranging between **27% and 31% from 2017 to 2023**, before gradually declining to **22.11% in 2025 and 19.21% in 2026**. This earlier stability suggests that a significant portion of African developers engaged in core machine learning experimentation alongside linguistic work. However, the slight share decline in the most recent years may reflect the explosive growth of Applied and Data Engineering categories, which expanded more rapidly in relative terms.

The **Applied cluster shows a clear upward trend in share over time**. From less than 3% in the early 2010s, it rises to **3.56% in 2023**, **5.34% in 2024**, **7.83% in 2025**, and **9.28% in 2026**. This steady increase indicates growing sectoral deployment of AI solutions across industries. The acceleration suggests that AI is transitioning from experimentation toward real-world implementation, particularly in start-up-driven environments.

Similarly, the **Data Engineering cluster demonstrates gradual share growth**, rising from minimal levels in early years to **5.26% in 2023**, before stabilizing around **3–4% in 2025–2026**. This indicates increasing recognition of the importance of data infrastructure to support AI systems. Although still relatively small compared to Linguistic and Foundational clusters, the upward movement suggests ecosystem maturation.

The **MLOps cluster remains small but shows incremental growth in recent years**, increasing from near-zero levels in early years to **0.66% in 2023**, **0.76% in 2024**, and **1.40% in 2026**. This gradual rise signals early movement toward production-level deployment and lifecycle management, which typically emerges in more mature AI ecosystems.

The **Evaluation and Governance clusters remain consistently low throughout the period**, each generally below 1% annually. Their shares show minimal long-term growth, indicating that systematic model auditing, bias evaluation, and regulatory tooling are still underdeveloped within open-source repositories. Governance peaks remain small and do not display sustained upward trajectories comparable to Applied or Data Engineering.

Overall, the temporal patterns reveal a dual structure. First, **Linguistic AI remains the dominant and structurally stable backbone of African AI repository activity**, consistently representing the majority of contributions. Second, there is clear evidence of **gradual diversification**, particularly in Applied AI, Data Engineering, and MLOps, especially from 2023 onward. The rapid expansion in total repositories during this period amplifies these shifts, suggesting ecosystem maturation rather than simple volume growth.

In summary, there are meaningful year-on-year trend changes. While linguistic AI continues to dominate, the ecosystem is slowly broadening toward application deployment, infrastructure development, and operational maturity. The data indicate that African AI communities are evolving from primarily language-focused experimentation toward a more diversified and increasingly production-oriented structure. Table 6 offers the overall Synthesis of AI Capability Production: Open-Source and Developer Ecosystems.

Table 6: Overall Synthesis of AI Capability Production: Open-Source and Developer Ecosystems

Question	Evidence-Based Conclusion
Where is capability built?	● AI capability (GitHub repositories, 27,349 total) is **highly geographically concentrated in West Africa (53.14%)**, followed by **North Africa (19.66%)** and **East Africa (11.50%)**. ● At the country level, **Ghana leads with 30.58%**, followed by **Nigeria (13.31%)** and **Egypt (11.52%)**. ● The top three countries together account for **55.41% of total repositories**, indicating strong national concentration.
What skills dominate?	● Skill production is overwhelmingly concentrated in **Linguistic AI (63.98%)**, followed by **Foundational AI (25.51%)**. Together, these two clusters account for **89.49% of all repositories**, while Applied (5.13%), Data Engineering (3.65%), MLOps (0.82%), Evaluation (0.63%), and Governance (0.29%) collectively represent just **10.51%**.
Is it linguistic, applied, or evaluative?	● African AI capability is **predominantly linguistic**. The Linguistic cluster alone represents **63.98%** of activity, far exceeding Applied (5.13%) and Evaluation (0.63%). This indicates that AI production is mainly centered on language technologies, localization, and generative AI adaptation rather than sectoral deployment or systematic evaluation.
Are communities maturing?	● Yes. Temporal trends show rapid expansion: repositories increased from **2 (2009)** to **9,598 (2025)**. ● Growth accelerated sharply after 2020, particularly in Applied, Data Engineering, and MLOps clusters. ● Regionally, diversification is occurring: West Africa's share declined from **~75–80% in early years to ~41.6% in 2025**, while North and East Africa increased their shares. This indicates **ecosystem expansion and gradual structural maturation**, though linguistic dominance remains strong.

CHAPTER 8: ALIGNMENT GAPS: DEMAND, KNOWLEDGE, AND CAPABILITY

This chapter synthesizes the three foundational pillars of Africa's AI ecosystem: 9,937 AI job postings (demand), 25,489 AI research publications (knowledge production), and 27,349 AI GitHub repositories (capability production). While the preceding chapters examined each pillar independently, this section moves beyond descriptive analysis to evaluate whether these components are evolving in structural harmony or diverging in ways that may constrain long-term ecosystem development.

By systematically comparing these three continental totals (AI job postings (demand), AI research publications (knowledge production), and GitHub repositories (capability production)) across regions, countries, skill clusters, and time, the chapter assesses the degree of coherence within Africa's AI landscape. Labour demand reflects where AI is being economically absorbed; research publications indicate where intellectual and scientific capacity is being generated; and GitHub repositories reveal where practical technical capability is actively being built. Alignment among these pillars suggests an integrated innovation system. Misalignment, by contrast, signals structural gaps that may limit scalability, commercialization, or inclusive growth.

The analysis identifies areas where job demand exceeds local capability production, indicating potential talent shortages or reliance on external expertise. It also highlights cases where research output outpaces market absorption, suggesting academic strength without proportional industrial integration. Conversely, it examines instances where open-source development is heavily concentrated relative to economic demand, reflecting strong grassroots technical engagement that may not yet be fully translated into formal employment or commercial ecosystems. Temporal analysis further evaluates whether growth trajectories across demand, research, and capability are synchronized or diverging over time.

Ultimately, this chapter addresses the central strategic question of the report: Are Africa's 9,937 AI jobs, 25,489 research publications, and 27,349 repositories evolving in alignment, or do measurable structural gaps exist between demand, knowledge creation, and capability development? By answering this question, the chapter provides a diagnostic assessment of the continent's AI ecosystem maturity and offers insight into where policy, investment, and institutional coordination may be most urgently required.

8.1. AI Talent Production vs Demand (Region)

Table 7 presents the AI Talent Production vs Demand (Regional Comparison). Regionally, Africa's AI ecosystem shows clear structural imbalance between where jobs are concentrated and where digital capability is being built.

Table 7: AI Talent Production vs Demand (Regional Comparison)

Region	Jobs Demand Share	GitHub Capability Share	Research Publication Share	Alignment Gap
North Africa	37.25%	19.66%	29.99%	High demand but lower capability contribution; research relatively strong but still below demand weight.
West Africa	20.61%	53.14%	29.37%	Major capability hub; supply far exceeds job demand share. Strong overproduction in GitHub.
Southern Africa	19.67%	7.43%	17.76%	Demand moderately aligned with research; capability contribution comparatively low.
East Africa	16.11%	11.50%	16.71%	Relatively balanced across demand and research; slight underrepresentation in GitHub.
Central Africa	6.35%	8.28%	6.17%	Small market but slightly overperforming in GitHub relative to demand.

- **North Africa dominates job demand (37.25%)**, yet its GitHub capability share (19.66%) is substantially lower. This indicates that while the region hosts strong formal labour demand, open-source AI production is relatively underrepresented compared to its economic weight. However, North Africa's research output (29.99%) is closer to its demand share, suggesting stronger academic–industry linkage than in other regions.
- In contrast, **West Africa overwhelmingly dominates GitHub capability (53.14%)**, far exceeding its job demand share (20.61%). This indicates a **major over-concentration of open-source AI development activity**, especially driven by countries such as Ghana and

Nigeria. While this reflects strong grassroots developer ecosystems, it does not directly translate into proportional formal job demand within the region. West Africa therefore functions as the continent's primary digital production hub, even though it is not the largest formal employment market.

- **Southern Africa presents moderate demand (19.67%) but relatively low GitHub capability (7.43%)**, indicating a potential underperformance in open-source production relative to market size. However, its research output (17.76%) is much closer to demand, suggesting that academic production is more aligned with economic demand than developer-led open innovation.
- **East Africa demonstrates relative balance**, with job demand (16.11%) closely matching research output (16.71%) and slightly lower GitHub share (11.50%). This suggests a comparatively integrated ecosystem, though capability production could still expand.
- Finally, **Central Africa remains small across all dimensions**, though its GitHub share (8.28%) slightly exceeds its job demand share (6.35%), indicating modest but emerging digital activity relative to economic size.

8.1.1 Overall Regional Conclusion

The African AI ecosystem is not geographically aligned across demand, research, and open-source capability, but instead exhibits clear regional specialization. North Africa is demand-driven, accounting for the largest share of AI job postings; West Africa dominates open-source capability, contributing the highest proportion of GitHub repositories; Southern Africa maintains a comparatively strong research base but weaker developer production; East Africa shows relative balance across pillars; and Central Africa remains small, though slightly capability-positive relative to demand. This pattern reveals a structural alignment gap in which the regions generating the most digital capability are not necessarily those with the strongest labor market demand, highlighting fragmentation within the continent's AI ecosystem.

8.2. AI Talent Production vs Demand at Country Level

To assess alignment at the country level, we compare **Jobs Demand Share**, **GitHub Capability Share**, and **AI Research Publication Share** for the **top 10 countries by demand** (from your earlier job-demand distribution). This allows us to evaluate whether labour market demand aligns with open-source production and academic output. Table 8 presents the AI Talent Production vs Demand at Country Level.

Table 8: AI Talent Production vs Demand at Country Level

Country	Jobs Demand Share	GitHub Capability Share	Research Publication Share	Alignment Gap)
South Africa	16.39%	4.38%	9.48%	High demand but much lower GitHub share; moderate research alignment.
Morocco	13.67%	2.16%	11.05%	Strong demand and research; capability production significantly lower.
Egypt	13.64%	11.52%	6.27%	Relatively balanced; strong demand with moderate GitHub presence.
Nigeria	10.93%	13.31%	14.06%	Strong alignment; capability and research exceed demand share.
Kenya	8.17%	4.66%	2.39%	Demand exceeds both GitHub and research output.
Tunisia	6.84%	1.13%	5.23%	Demand relatively well supported by research; weak GitHub production.
Algeria	2.94%	2.60%	6.67%	Research strong relative to demand; capability slightly aligned.
Ghana	6.26%	30.58%	10.02%	Major over-concentration of GitHub capability compared to demand.
Democratic Republic of the Congo	4.19%	4.46%	0.24%	Capability slightly aligned; research extremely low relative to demand.
Ethiopia	1.78%	2.40%	5.39%	Research output exceeds demand; capability modestly aligned.

- At the country level, **alignment is uneven and highly concentrated**. **South Africa and Morocco dominate job demand**, yet their GitHub capability shares are comparatively much lower. This indicates that although these countries represent major AI labour markets, open-source AI production is not proportionally distributed within them. Their research output, however, is closer to demand—especially in Morocco—suggesting stronger academic ecosystems relative to developer-led open innovation.
- **Nigeria and Ghana stand out as major capability hubs.** Nigeria demonstrates strong alignment across all three dimensions, with GitHub (13.31%) and research (14.06%)

exceeding its job demand share (10.93%). This indicates a mature ecosystem where knowledge production and developer activity are strongly integrated. Ghana shows an even more pronounced pattern: while its job demand share is moderate (6.26%), its GitHub contribution is extremely high (30.58%), reflecting substantial over-concentration in open-source development relative to formal labour demand.

- **Egypt shows relatively balanced performance**, with strong demand (13.64%) and substantial GitHub contribution (11.52%), though research output is comparatively lower than expected given its market size. This suggests potential for scaling academic production.

  Though, a**n** important theme from the interviews concerns the **mismatch between talent availability, labour market experience, and employment opportunities**. For instance, one of the participants emphasises (00:10:35) that Egypt possesses a **large pool of technically skilled individuals**, but many of them are **fresh graduates with limited industry experience**. As noted in the interview, *"we have raw skills… a very big body of talent, but as raw skills."* This suggests that although universities and training programmes produce technically capable graduates, the transition from education to employment remains challenging.

- Countries such as **Kenya and Tunisia exhibit demand that exceeds their capability contributions**, indicating room for expansion in open-source ecosystems. Meanwhile, **Ethiopia and Algeria show research strength relative to demand**, suggesting that academic systems may be slightly ahead of market absorption capacity.

8.2.1 Overall Country-Level Conclusion

At the national level, Africa's AI ecosystem is highly uneven. A small number of countries dominate across dimensions, but the pattern differs by pillar: Demand Leaders: South Africa, Morocco, Egypt, Nigeria, while GitHub Capability Leaders: Ghana, Nigeria, Egypt. Also, Research Leaders: Nigeria, Morocco, Ghana, South Africa. The alignment analysis shows that Nigeria is the most structurally balanced ecosystem, while Ghana is heavily capability-concentrated, and South Africa and Morocco are demand-dominant economies with relatively lower open-source production intensity. This confirms that Africa's AI landscape is concentrated but asymmetrically aligned across supply and demand structures, creating measurable alignment gaps.

8.3. AI Talent Production vs Demand across Skill Cluster

To assess alignment at the skill level, we compare AI Jobs Demand, GitHub Capability (Talent Repositories), and AI Research Publications across the seven skill clusters. This helps determine whether Africa's technical production ecosystem is aligned with labour-market needs. Table 9 presents the AI Talent Production vs Demand across Skill Cluster.

Table 9: AI Talent Production vs Demand across Skill Cluster

Skill Cluster	Jobs Demand Share (%)	GitHub Capability Share (%)	Research Share (%)	Alignment Gap
FOUNDATIONAL	23.62%	25.51%	34.44%	Strong alignment; dominant across all three pillars. Research-heavy ecosystem.
LINGUISTIC	11.45%	63.98%	18.08%	Highly over-concentrated in capability; dominant in GitHub production.
APPLIED	14.22%	5.13%	26.74%	Research exceeds demand; capability significantly underrepresented.
DATA_ENG	16.77%	3.65%	14.47%	Demand moderately aligned with research; capability low relative to need.
EVALUATION	14.16%	0.63%	3.37%	Underrepresented across both capability and research relative to demand.
GOVERNANCE	13.53%	0.29%	2.71%	Severe structural gap; weak production despite significant demand.
MLOPS	6.26%	0.82%	0.18%	Extremely underdeveloped; minimal presence in all ecosystems.

- The skill-level comparison reveals a **structural imbalance in Africa's AI ecosystem**. The most striking pattern is the dominance of **LINGUISTIC capability**, which accounts for **63.98% of GitHub repositories**, far exceeding its job demand share (11.45%) and research share (18.08%). This indicates a strong open-source orientation toward language-based AI development, potentially driven by NLP projects, multilingual challenges, and data availability patterns across the continent.

- In contrast, **FOUNDATIONAL AI is the most balanced cluster**, with strong representation in jobs (23.62%), research (34.44%), and capability (25.51%). This suggests that foundational technologies—such as core machine learning methods—form the backbone of Africa's AI production and are relatively well aligned with market needs.
- However, significant gaps exist in **GOVERNANCE, EVALUATION, and MLOPS**. Although governance-related roles account for 13.53% of job demand, GitHub representation is extremely low (0.29%), and research output is also minimal (2.71%). This indicates a structural shortage in AI ethics, policy, compliance, and system management capabilities. Similarly, **MLOPS is critically underdeveloped**, representing only 0.82% of capability and 0.18% of research, despite growing industrial demand for operational AI deployment.
- The data therefore show that Africa's AI ecosystem is **not evenly aligned across skills**. While linguistic AI and foundational methods dominate production, operational, governance, and evaluation capacities lag behind demand. This pattern suggests an ecosystem that is **research- and prototype-oriented**, but not yet fully matured in deployment, regulation, and system-scale implementation.

8.3.1 Overall Skill-Level Conclusion

African AI production is **highly concentrated in Linguistic and Foundational clusters**, moderately aligned in core machine learning areas, and structurally underdeveloped in **Governance, Evaluation, and MLOPS**. The imbalance indicates both specialization strengths and strategic gaps that may limit industrial scaling and responsible AI deployment.

8.4. Temporal Alignment: AI Talent Production vs Demand (Over Time)

To evaluate temporal alignment, we compare the **growth trajectory of AI Jobs Demand** with the **growth trajectory of GitHub AI Talent Repositories** across the same general period. The objective is to determine whether capability production is keeping pace with market demand or whether a widening gap is emerging.

1. Growth in AI Jobs Demand (Time Trend)

AI job postings show a clear acceleration, particularly after 2020. Demand increased from modest levels in earlier years to a strong expansion phase in the most recent period. The sharpest growth occurred in the post-2020 period, with job volumes rising substantially year-on-year. This indicates a rapidly expanding AI labour market across Africa, with especially strong momentum in recent years. The trend demonstrates that AI employment demand is **structurally expanding**, not cyclical. The growth pattern suggests increasing institutional adoption, enterprise AI integration, and cross-sector digitisation.

2. Growth in AI Talent Repositories (GitHub Capability)

GitHub-based AI capability shows an even more dramatic expansion trajectory. Repository creation remained relatively modest before 2016, then accelerated sharply from 2017 onward. The most notable surge occurred in **2024–2025**, where repository creation increased exponentially compared to earlier years. This indicates that Africa's open-source AI ecosystem has entered a phase of **rapid community scaling**, particularly in recent years. The acceleration suggests increasing developer engagement, improved digital infrastructure, and stronger participation in global AI collaboration networks.

3. Temporal Alignment Between Demand and Capability

When comparing both trends, several patterns emerge. First, **capability growth appears to be outpacing job demand growth in recent years**, especially in the 2024–2025 period. The scale of GitHub repository expansion is substantially larger than the proportional increase in job postings. This suggests that developer-side activity is accelerating faster than formal labour-market absorption.

Second, the temporal pattern indicates a **lag structure**: capability expansion intensifies first, followed by job demand growth. **This is consistent with innovation diffusion theory, where open-source experimentation often precedes large-scale commercial adoption**.

Third, both demand and capability show strong upward trajectories, meaning the system overall is expanding rather than stagnating. However, the rate of capability expansion in recent years suggests a possible **future surplus of technical production relative to current job absorption capacity**, unless enterprise adoption continues accelerating.

4. Is There Temporal Concentration?

Yes. The data clearly show **temporal concentration in the most recent years (2020–2025)** for both demand and capability. A substantial share of total activity occurs in this short window, indicating that Africa's AI ecosystem is not historically flat but has undergone a rapid growth phase in the last five years. This concentration suggests an ecosystem currently in a **scaling phase**, transitioning from early adoption to broader institutionalisation.

8.4.1 Overall Temporal Conclusion

The evidence shows that Africa's AI ecosystem is **rapidly growing on both the demand and capability sides**, with particularly strong acceleration since 2020. GitHub-based AI production has expanded sharply, and job demand has also risen significantly. Importantly, **capability growth is currently outpacing demand growth**, indicating strong developer momentum. However, continued alignment will depend on whether industry adoption, investment, and institutional AI integration expand at a similar rate. In summary, the temporal trend reflects a **dynamic and rapidly maturing ecosystem**, rather than a stagnant or declining one.

8.5 AI Talent Priority Gap Analysis (Survey-Based Evidence)

This section extends the structural alignment analysis by incorporating survey-based evidence on AI talent priorities across Africa. While the preceding sections of Chapter 4 evaluated alignment gaps using quantitative ecosystem signals—9,937 AI job postings (demand), 25,489 research publications (knowledge production), and 27,349 GitHub repositories (capability production)—this extension introduces a perception-based diagnostic layer. The objective is to capture how ecosystem stakeholders assess current importance, future importance, availability, and geographic distribution of AI skills, thereby identifying priority gaps that may not be fully visible in platform-based datasets.

The survey framework evaluates each of the seven AI skill clusters using a structured scoring model. Respondents assessed current importance, projected importance, availability across the continent, geographic spread, and confidence levels. From these inputs, an Importance Growth rate was calculated to capture expected trajectory shifts, and a Priority Gap Score was derived to ensures that skills perceived as highly important but scarce receive higher priority scores, allowing for a systematic identification of structural capability shortages. Scores are then categorized into Critical, High, Moderate, or Low priority bands to enable comparative interpretation across regions.

The analysis is conducted at two levels. First, an overall continental assessment provides a macro-level view of which skill clusters represent Africa-wide priority gaps. Second, regional breakdowns for Central, East, North, Southern, and West Africa identify geographically differentiated pressures within the ecosystem. This dual-layer approach allows the report to distinguish between continent-wide structural shortages and region-specific talent constraints.

Importantly, this section does not replace the quantitative alignment findings but complements them. By juxtaposing survey-based priority gaps with observed distributions in jobs, research, and GitHub production, the analysis assesses whether perceived shortages align with measured structural imbalances. This comparison strengthens the strategic relevance of Chapter 4 by linking data-driven ecosystem mapping with stakeholder-informed priority signals.

Through this integration, the chapter moves beyond diagnosing where misalignment exists to identifying where intervention may be most urgent. The inclusion of Priority Gap Scores therefore provides a forward-looking, policy-relevant layer to the broader alignment analysis, enabling targeted recommendations for capacity building, investment, and ecosystem coordination.

8.5.1 Continental Assessment of AI Talent Priority Gap

Table 10 shows the continental assessment of AI Talent Priority Gap. The table presents a multidimensional assessment of Africa's AI skill landscape by combining perceptions of importance with measures of availability and distribution. Each column contributes a distinct analytical lens, allowing the Priority Gap Score to reflect both **urgency and scarcity** rather than importance alone.

Table 10: Continental Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated, 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	3.1	4.4	2.2	2.0	3.6	41.3%	11.7	Moderate priority
Data Engineering for AI	4.5	4.7	3.8	3.8	3.7	5.8%	10	Moderate priority
Linguistic & Cultural Expertise	3.7	4.1	3.1	2.9	3.0	9.8%	10.8	Moderate priority
Evaluation & Quality Assurance	3.2	4.0	1.9	2.5	3.4	25.4%	13.1	High priority
Applied Product, Analytics & Deployment	4.5	4.8	3.7	3.3	3.8	6.8%	10.2	Moderate priority
Governance, Ethics & Safety	3.8	4.5	3.0	2.8	3.4	18.5%	11.5	Moderate priority
MLOps/LLM Ops	3.7	4.2	2.9	2.1	3.2	13.0%	11.5	Moderate priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

The **Current Importance** score captures how stakeholders rate the present relevance of each skill cluster on a scale from low to critical. Applied Product, Analytics & Deployment and

Data Engineering for AI both record the highest current importance score of 4.5, indicating that market-facing and infrastructure-oriented capabilities are already central to Africa's AI ecosystem. Governance, Ethics & Safety (3.8) and MLOps/LLMOps (3.7) also demonstrate strong present relevance. In contrast, Foundational AI/LLM Engineering (3.1) and Evaluation & Quality Assurance (3.2) are perceived as moderately important at present, suggesting that advanced model development and structured evaluation functions are still emerging rather than fully embedded across markets.

The **Projected Importance** reflects expected future criticality. All clusters experience upward movement, but the magnitude varies. Applied Product, Analytics & Deployment rises to 4.8, while Data Engineering increases to 4.7, reinforcing expectations that infrastructure and deployment capabilities will remain foundational. Notably, Foundational AI/LLM Engineering jumps from 3.1 to 4.4, indicating strong anticipated growth in advanced model-building capabilities. Evaluation & Quality Assurance increases from 3.2 to 4.0, signalling recognition that structured validation and benchmarking will become more central as AI systems scale across sectors.

The **Importance Growth** quantifies percentage change between current and projected importance. Foundational AI/LLM Engineering exhibits the highest growth rate at 41.3 percent, underscoring expectations of rapid structural expansion in advanced AI capabilities. Evaluation & Quality Assurance follows with 25.4 percent growth, signalling accelerating recognition of quality assurance needs. Governance, Ethics & Safety (18.5 percent) and MLOps/LLMOps (13.0 percent) also show forward momentum, reflecting governance and operational maturity pressures. In contrast, Data Engineering (5.8 percent) and Applied Product (6.8 percent) demonstrate stability rather than acceleration, suggesting they are already embedded pillars rather than emerging gaps.

The **Availability Across the Continent** measures perceived supply depth. Data Engineering (3.8) and Applied Product (3.7) show relatively stronger availability, implying that applied and data infrastructure skills are comparatively more distributed across African markets. By contrast, Evaluation & Quality Assurance records the lowest availability score at 1.9, indicating widespread scarcity. Foundational AI/LLM Engineering also remains limited at 2.2. These low availability scores are critical drivers of the overall Priority Gap calculations.

The **Geographical Spread** assesses distribution breadth rather than volume. Data Engineering (3.8) again shows wider continental dispersion, while Foundational AI/LLM Engineering (2.0) and MLOps/LLMOps (2.1) appear geographically concentrated. Evaluation & Quality Assurance (2.5) remains limited in spread, reinforcing the interpretation that validation and benchmarking capacity is not yet evenly institutionalized across regions.

The **Confidence Level** indicates respondent certainty in their assessments. Scores cluster between 3.0 and 3.8, suggesting moderate-to-high confidence overall. Applied Product (3.8) and Data Engineering (3.7) attract relatively strong confidence, likely reflecting clearer market visibility. Linguistic & Cultural Expertise records a slightly lower confidence level (3.0), which may indicate variability across countries or evolving interpretations of its scope.

The **Priority Gap Score** integrates urgency and scarcity. Evaluation & Quality Assurance records the highest score at 13.1, placing it in the High priority category in the overall Africa assessment. This outcome reflects its combination of rising importance and very low availability. Foundational AI/LLM Engineering (11.7), Governance, Ethics & Safety (11.5), and MLOps/LLMOps (11.5) cluster near the upper bound of Moderate priority, indicating significant but not yet critical shortages. Data Engineering (10.0) and Applied Product (10.2), despite high importance, record moderate gap scores because availability is relatively stronger.

Finally, the **Priority Rating** translates numeric scores into actionable categories. Only Evaluation & Quality Assurance reaches High priority status at the continental level, while all other clusters fall within Moderate priority. This distribution suggests that Africa's most pressing ecosystem-wide gap is not basic AI application capacity, but rather the institutionalization of evaluation, validation, and quality control systems. The broader pattern indicates a continent where applied AI capabilities are relatively established, forward-looking foundational engineering is accelerating, and evaluation mechanisms represent the most acute structural constraint.

Together, the findings reveal a nuanced ecosystem dynamic: importance is rising across all clusters, but scarcity and concentration vary significantly. The most urgent priorities emerge where projected growth intersects with limited availability, rather than where importance alone is high.

8.5.2 Central Africa Assessment of AI Talent Priority Gap

The Central Africa results reveal a structurally constrained but rapidly intensifying AI skills landscape. Across all seven clusters, projected importance reaches the maximum score of 5.0, indicating unanimous expectations that every core AI capability will become critical in the near future. This universal upward projection immediately differentiates Central Africa from the continental average, where projected importance varies across clusters. In Central Africa, the issue is not selective specialization but broad-based urgency. Table 11 shows the Central Africa assessment of AI talent priority gap.

Table 11: Central Africa Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated, 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/ Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	3.0	5.0	2.0	2.0	5.0	66.7%	12	High priority
Data Engineering for AI	4.0	5.0	2.0	2.0	4.0	25.0%	16	High priority
Linguistic & Cultural Expertise	4.0	5.0	3.0	3.0	4.0	25.0%	12	High priority
Evaluation & Quality Assurance	3.0	5.0	1.0	1.0	4.0	66.7%	15	High priority
Applied Product, Analytics & Deployment	4.0	5.0	3.0	3.0	5.0	25.0%	12	High priority
Governance, Ethics & Safety	3.0	5.0	2.0	2.0	4.0	66.7%	12	High priority
MLOps/LLMOps	3.0	5.0	1.0	1.0	4.0	66.7%	15	High priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

The **Current Importance** scores range between 3.0 and 4.0, suggesting that AI capabilities are presently viewed as moderately to highly important but not yet fully embedded across sectors. Data Engineering, Linguistic & Cultural Expertise, and Applied Product, Analytics & Deployment register stronger current relevance (4.0), while Foundational AI/LLM Engineering, Evaluation & Quality Assurance, Governance, and MLOps are rated at 3.0. This indicates that while application-oriented functions have begun to take root, advanced engineering, operationalization, and evaluation systems remain in formative stages.

The most striking pattern emerges in the **Projected Importance** and **Importance Growth** columns. Foundational AI/LLM Engineering, Evaluation & Quality Assurance, Governance, and MLOps each record a 66.7 percent increase in importance, representing the highest growth rates within the region. Data Engineering, Linguistic & Cultural Expertise, and Applied Product functions show 25 percent growth, still substantial but comparatively more stable. These figures signal a structural transition phase in which Central Africa anticipates a rapid scaling of both technical depth and institutional governance capacity.

However, this rising importance is counterbalanced by weak **Availability** and **Geographical Spread** scores. Evaluation & Quality Assurance and MLOps record the lowest availability (1.0) and minimal geographic spread (1.0), indicating acute scarcity and extreme concentration. Foundational AI/LLM Engineering, Governance, and Data Engineering also show limited availability (2.0) and narrow distribution (2.0). Even Linguistic & Cultural Expertise and Applied Product functions, which score slightly higher at 3.0 for availability and spread, remain only moderately distributed. This pattern reflects a region where AI talent pools are thin and highly localized.

The **Confidence Level** scores, ranging from 4.0 to 5.0, are notably high. Respondents express strong certainty in their assessments, particularly regarding Foundational AI/LLM Engineering and Applied Product capabilities, both receiving a confidence score of 5.0. This suggests that the perceived shortages are not speculative but grounded in observable ecosystem realities.

These dynamics translate directly into elevated **Priority Gap Scores**. All seven clusters fall within the High priority category (12–19). Data Engineering records the highest gap score at 16, reflecting its combination of critical projected importance and limited availability. Evaluation & Quality Assurance and MLOps follow closely at 15, driven by extremely low availability. Foundational AI/LLM Engineering, Linguistic & Cultural Expertise, Applied Product functions, and Governance each score 12, reinforcing the conclusion that shortages are systemic rather than isolated.

Overall, Central Africa exhibits a comprehensive capability deficit under conditions of accelerating demand. Unlike regions where gaps are concentrated in specific clusters, Central Africa faces broad-spectrum talent shortages across engineering, deployment, governance, and evaluation functions. The region's AI ecosystem is therefore characterized not by selective misalignment but by structural under-capacity relative to projected strategic importance.

8.5.3 East Africa Assessment of AI Talent Priority Gap

The East Africa results reveal a differentiated and strategically evolving AI ecosystem, characterized by targeted capability pressures rather than systemic shortages across all clusters. Unlike Central Africa, where urgency is uniform, East Africa displays clear prioritization, with certain functions emerging as critical bottlenecks while others remain moderately aligned. Table 12 shows the East Africa Assessment of AI talent priority gap.

Table 12: East Africa Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated, 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	3.0	3.5	2.5	1.5	3.0	16.7%	10.5	Moderate priority
Data Engineering for AI	4.0	4.5	2.5	2.0	3.0	12.5%	14	High priority
Linguistic & Cultural Expertise	4.0	4.5	3.0	2.5	2.5	12.5%	12	High priority
Evaluation & Quality Assurance	4.5	5.0	1.5	1.5	2.5	11.1%	20.3	Critical (Top Priority)
Applied Product, Analytics & Deployment	4.5	5.0	2.5	2.5	3.0	11.1%	15.8	High priority
Governance, Ethics & Safety	3.5	4.5	3.0	3.0	2.5	28.6%	10.5	Moderate priority
MLOps/LLMOps	2.5	4.5	2.0	1.5	1.5	80.0%	10	Moderate priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

In terms of **Current Importance**, Evaluation & Quality Assurance and Applied Product, Analytics & Deployment register the highest scores at 4.5, indicating that both validation systems and market-facing deployment capabilities are already central to the region's AI ecosystem. Data Engineering and Linguistic & Cultural Expertise follow closely at 4.0, reflecting the operational and contextual backbone of AI implementation. Foundational AI/LLM Engineering (3.0) and Governance, Ethics & Safety (3.5) are moderately important at present, while MLOps/LLMOps records the lowest current importance at 2.5, suggesting that operational scaling mechanisms are still emerging.

Projected Importance scores increase across all clusters, with Evaluation & Quality Assurance and Applied Product functions reaching the maximum score of 5.0. Governance rises significantly from 3.5 to 4.5, while MLOps increases sharply from 2.5 to 4.5. Although Foundational AI/LLM Engineering grows more modestly to 3.5, the overall pattern signals ecosystem deepening, particularly in evaluation, governance, and operationalization layers.

The **Importance Growth** column reinforces this trajectory. MLOps/LLMOps records the highest growth rate at 80 percent, indicating strong anticipated scaling needs. Governance grows by 28.6 percent, while Data Engineering and Linguistic & Cultural Expertise increase by 12.5 percent. Evaluation & Quality Assurance and Applied Product functions show steady growth at 11.1 percent, suggesting that while already highly valued, their importance will further consolidate rather than surge.

Despite these rising expectations, **Availability** and **Geographical Spread** remain constrained in key areas. Evaluation & Quality Assurance records very low availability (1.5) and narrow geographic distribution (1.5), revealing acute scarcity. MLOps also remains limited, with availability at 2.0 and spread at 1.5. Data Engineering and Applied Product functions, while moderately available (2.5), are not yet widely dispersed. Linguistic & Cultural Expertise and Governance demonstrate slightly stronger availability and spread (3.0), suggesting somewhat broader institutional embedding.

These structural conditions translate directly into the **Priority Gap Scores**. Evaluation & Quality Assurance emerges as the only Critical gap, with a score of 20.3, the highest across all East African clusters. This reflects its combination of maximum projected importance and severe scarcity. Applied Product functions follow with a High priority score of 15.8, while Data Engineering (14) and Linguistic & Cultural Expertise (12) also fall within the High category. Foundational AI/LLM Engineering, Governance, and MLOps register Moderate priority levels, despite strong projected growth in some cases, because their current importance or calculated scarcity produces comparatively lower composite scores.

Confidence levels are generally moderate, ranging from 1.5 to 3.0, slightly lower than in some other regions. This may reflect variability across countries within East Africa or differing maturity levels in national AI ecosystems.

Overall, East Africa's profile suggests a region where applied AI and evaluation functions are central but under-supplied, creating targeted high-pressure zones. The most critical structural constraint lies in Evaluation & Quality Assurance, indicating that as AI deployment expands, the region risks scaling without sufficient benchmarking, testing, and validation infrastructure. Unlike Central Africa's broad capability deficit, East Africa exhibits a concentrated alignment gap centered primarily on quality assurance and deployment capacity under accelerating growth conditions.

8.5.4 North Africa Assessment of AI Talent Priority Gap

The North Africa results present a comparatively mature and structurally balanced AI ecosystem. Unlike Central and East Africa, where sharp shortages or critical bottlenecks emerge, North Africa exhibits moderate alignment across all seven skill clusters. No cluster reaches High or Critical priority status, and all Priority Gap Scores fall within the Moderate band, indicating that while improvement is needed, the region does not face acute systemic deficits. Table 13 shows the North Africa Assessment of AI talent priority gap.

Table 13: North Africa Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated, 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/ Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	3.4	4.0	3.2	3.0	3.6	17.6%	9.5	Moderate priority
Data Engineering for AI	4.4	4.6	3.8	4.0	4.2	4.5%	9.7	Moderate priority
Linguistic & Cultural Expertise	3.4	3.8	3.2	3.2	3.0	11.8%	9.5	Moderate priority
Evaluation & Quality Assurance	3.8	3.8	3.2	3.2	3.4	0.0%	10.6	Moderate priority
Applied Product, Analytics & Deployment	4.4	4.6	4.2	4.4	4.2	4.5%	7.9	Moderate priority
Governance, Ethics & Safety	3.2	4.0	3.0	3.4	3.6	25.0%	9.6	Moderate priority
MLOps/LLMOps	3.8	4.0	3.6	4.0	3.8	5.3%	9.1	Moderate priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

In terms of **Current Importance**, Data Engineering for AI and Applied Product, Analytics & Deployment lead at 4.4, reflecting a strong market-oriented and infrastructure-driven AI landscape. Evaluation & Quality Assurance (3.8) and MLOps/LLMOps (3.8) are also well embedded, suggesting operational maturity. Foundational AI/LLM Engineering and Linguistic & Cultural Expertise record moderate scores of 3.4, while Governance, Ethics & Safety stands at 3.2, indicating steady but not dominant institutional emphasis.

Projected Importance rises modestly across most clusters. Data Engineering and Applied Product functions increase slightly to 4.6, reinforcing their sustained centrality. Foundational Engineering and Governance both rise to 4.0, with Governance showing a relatively strong growth rate of 25 percent. Evaluation & Quality Assurance remains stable at 3.8, showing zero growth, which suggests that stakeholders perceive its importance as already established rather than accelerating. Overall, Importance Growth rates are moderate, with most clusters showing single-digit or low double-digit increases, reflecting incremental strengthening rather than structural transformation.

Availability and Geographical Spread scores are notably higher than in other regions. Applied Product capabilities record availability at 4.2 and geographic spread at 4.4, the strongest distribution profile in the table. Data Engineering (3.8 availability; 4.0 spread) and MLOps (3.6 availability; 4.0 spread) also demonstrate broad institutional presence. Even clusters with moderate availability, such as Foundational Engineering (3.2) and Linguistic Expertise (3.2), are not severely constrained. This distribution pattern explains why Priority Gap Scores remain contained despite rising projected importance.

Confidence Levels are consistently strong, ranging between 3.0 and 4.2, with particularly high confidence in Data Engineering and Applied Product functions. This suggests that respondents perceive the ecosystem’s capability profile with relative clarity and stability.

The resulting **Priority Gap Scores** range from 7.9 to 10.6, all within the Moderate priority category. Evaluation & Quality Assurance records the highest score at 10.6, reflecting moderate scarcity combined with steady importance. Data Engineering (9.7), Governance (9.6), and Foundational Engineering (9.5) follow closely, but none approach the High priority threshold. Applied Product functions, despite high importance, record the lowest gap score (7.9) because of strong availability and wide spread.

Overall, North Africa demonstrates a relatively synchronized AI ecosystem where demand expectations and capability supply appear broadly aligned. The region does not exhibit critical skill shortages but rather incremental strengthening needs, particularly in governance and foundational engineering depth. Compared to other regions, North Africa’s profile suggests institutional consolidation rather than structural imbalance, positioning it as one of the continent’s more balanced AI capability environments.

8.5.5 Southern Africa Assessment of AI Talent Priority Gap

The Southern Africa results reflect the most mature and internally supplied AI skills ecosystem among the regions assessed. Unlike Central and East Africa, where scarcity drives high or critical priority gaps, Southern Africa demonstrates strong availability across most clusters, resulting in predominantly Low or Moderate priority ratings. The region's profile suggests consolidation rather than expansion under acute shortage conditions. Table 14 shows the Southern Africa Assessment of AI talent priority gap.

Table 14: Southern Africa Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated , 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/ Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	4.0	5.0	5.0	4.0	4.0	25.0%	4	Low priority
Data Engineering for AI	5.0	4.0	4.0	4.0	4.0	-20.0%	10	Moderate priority
Linguistic & Cultural Expertise	5.0	5.0	5.0	4.0	4.0	0.0%	5	Low priority
Evaluation & Quality Assurance	5.0	5.0	5.0	5.0	5.0	0.0%	5	Low priority
Applied Product, Analytics & Deployment	4.0	4.0	4.0	4.0	4.0	0.0%	8	Moderate priority
Governance, Ethics & Safety	5.0	5.0	4.0	3.0	4.0	0.0%	10	Moderate priority
MLOps/LLMOps	4.0	4.0	4.0	4.0	4.0	0.0%	8	Moderate priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

In terms of **Current Importance**, several clusters already register maximum or near-maximum scores. Data Engineering, Linguistic & Cultural Expertise, Evaluation & Quality Assurance, and Governance, Ethics & Safety all record scores of 5.0, indicating that these capabilities are fully embedded within the regional AI landscape. Foundational AI/LLM Engineering and Applied Product functions follow closely at 4.0, suggesting high but not yet absolute centrality. MLOps/LLMOps also stands at 4.0, reflecting operational maturity.

Projected Importance remains stable or reaches maximum levels across nearly all clusters. Foundational Engineering increases from 4.0 to 5.0, showing 25 percent growth, indicating strengthening emphasis on advanced model development. However, several clusters show zero growth, including Linguistic Expertise, Evaluation & Quality Assurance, Applied Product, Governance, and MLOps. Data Engineering is the only cluster that records a negative growth rate (−20 percent), declining from 5.0 to 4.0 in projected importance. This does not indicate declining relevance, but rather suggests stabilization or market saturation relative to other emerging needs.

Availability and Geographical Spread scores are consistently high. Foundational Engineering and Linguistic Expertise both record maximum availability (5.0), while Evaluation & Quality Assurance achieves both maximum availability (5.0) and maximum spread (5.0), indicating strong institutionalization and continental distribution within the region. Data Engineering, Applied Product, Governance, and MLOps also show solid availability (4.0) and widespread presence (3.0–4.0). This broad supply base explains the low Priority Gap Scores despite high importance levels.

Confidence Levels are uniformly strong, with most clusters rated at 4.0 and Evaluation & Quality Assurance at 5.0. This suggests that respondents perceive the ecosystem's capability distribution with high certainty and stability.

The resulting **Priority Gap Scores** reinforce this maturity profile. Foundational AI/LLM Engineering records a score of 4, placing it in the Low priority category despite its high projected importance, because availability is at maximum levels. Linguistic Expertise and Evaluation & Quality Assurance also register Low priority scores of 5. Data Engineering and Governance fall into the Moderate category at 10, reflecting some adjustment needs but not structural shortages. Applied Product and MLOps each score 8, also within Moderate priority.

Overall, Southern Africa presents a structurally aligned AI ecosystem where high importance is matched by strong availability and geographic spread. The absence of High or Critical priority gaps indicates that the region's talent base is relatively synchronized with anticipated demand. Rather than facing systemic shortages, Southern Africa's AI landscape appears to be in a phase of consolidation, optimization, and incremental rebalancing across clusters.

8.5.6 West Africa Assessment of AI Talent Priority Gap

The West African assessment presents a distinctive pattern in which AI capability demand is relatively high, yet the availability and geographical distribution of skills remain constrained, resulting in several High priority gaps. This outcome is particularly notable given that earlier analyses of open-source production showed that West Africa accounts for the largest share of AI GitHub repositories in Africa, indicating strong grassroots developer activity. However, the survey findings suggest that capability depth and ecosystem distribution remain uneven, creating structural shortages in several critical skill clusters. Table 15 presents the West Africa Assessment of AI talent priority gap.

Table 15: West Africa Assessment of AI Talent Priority Gap

AI Skill Cluster	Current Importance	Projected Importance	Availability Across the Continent	Geographical Spread	Confidence Level	Importance Growth	Priority Gap Score	Priority Rating
	(1 – low, 3 – moderate, 5 – critical)	*(1 – low, 3 – moderate, 5 – critical)*	*(1 – scarce, 5 – widely available)*	*(1 – concentrated, 5 – widespread)*	*(1 – Very Low, 5 –Very High)*	*Percentage Increase/ Decrease*	*1 to 25*	
Foundational AI/LLM Engineering	4.0	4.5	3.5	3.0	3.5	12.5%	10	Moderate priority
Data Engineering for AI	4.0	4.0	2.5	2.5	3.0	0.0%	14	High priority
Linguistic & Cultural Expertise	3.5	3.5	2.0	2.0	2.5	0.0%	14	High priority
Evaluation & Quality Assurance	4.0	4.0	2.5	2.5	3.0	0.0%	14	High priority
Applied Product, Analytics & Deployment	4.0	4.0	2.5	2.5	3.0	0.0%	14	High priority
Governance, Ethics & Safety	4.0	4.0	2.5	2.5	3.0	0.0%	14	High priority
MLOps/LLMOps	3.5	3.5	2.0	2.0	2.5	0.0%	14	High priority

Priority Rating: 20–25= Critical gap (Top priority), 12–19=High priority gap, 6–11=Moderate priority gap, 1–5=Low.

With respect to **Current Importance**, most clusters are rated between 3.5 and 4.0, indicating that stakeholders already perceive them as highly relevant to the regional AI ecosystem. Foundational AI/LLM Engineering, Data Engineering, Evaluation & Quality Assurance, Applied Product Development, and Governance all record a score of 4.0, reflecting strong operational demand. Linguistic & Cultural Expertise and MLOps/LLMOps receive slightly lower ratings of 3.5, suggesting moderate-to-high current importance but somewhat less centrality compared to infrastructure and deployment-oriented skills.

Looking ahead, **Projected Importance remains stable across most clusters**, with only Foundational AI/LLM Engineering showing an increase from 4.0 to 4.5 (12.5% growth). This indicates that stakeholders anticipate a gradual strengthening of advanced model development capabilities in the region. The absence of projected growth in the other clusters does not indicate declining relevance; rather, it suggests that these skills are already considered core requirements and will remain consistently important for AI ecosystem development.

The key constraint in the West African ecosystem appears in **Availability Across the Continent** and **Geographical Spread**. Availability scores range between 2.0 and 3.5, indicating that many skills are perceived as scarce or only moderately accessible. Linguistic Expertise and MLOps register the lowest availability scores at 2.0, suggesting a limited pool of specialized practitioners. Data Engineering, Evaluation, Applied Product, and Governance also score only 2.5 in availability, indicating that the supply of talent in these areas is insufficient relative to ecosystem needs. Geographical spread mirrors this limitation, with most clusters scoring between 2.0 and 3.0, implying that capabilities are concentrated in a small number of innovation hubs rather than distributed widely across the region.

Confidence levels range from 2.5 to 3.5, reflecting moderate certainty among respondents regarding these assessments. Foundational Engineering receives the highest confidence score (3.5), suggesting relatively stronger evidence regarding the status of this skill cluster. Linguistic Expertise and MLOps record lower confidence levels (2.5), indicating that respondents may perceive these areas as less well mapped or understood within the regional ecosystem.

These structural characteristics produce the **Priority Gap Scores**, which highlight the most pressing areas for intervention. Six of the seven clusters—Data Engineering, Linguistic Expertise, Evaluation & Quality Assurance, Applied Product Development, Governance & Ethics, and MLOps—each record a score of 14, placing them firmly within the **High priority**

gap category. These results suggest that although these skills are already important for the regional AI ecosystem, their limited availability and concentration significantly constrain ecosystem expansion. Foundational AI/LLM Engineering records a lower score of 10, falling within the **Moderate priority category**, primarily because availability (3.5) is relatively stronger than in other clusters.

Overall, the West African results reveal a **capability depth challenge rather than an absence of innovation activity**. The region demonstrates strong participation in open-source AI development, but the survey findings indicate that many critical capabilities remain concentrated in a small number of hubs and are not yet sufficiently widespread. Consequently, the ecosystem faces high-priority gaps across several technical and operational clusters that are essential for scaling AI deployment, governance, and production-ready systems across the region.

8.5.7 Overall Synthesis for continent-wide and sub-regional findings

Table 16 presents a concise synthesis table integrating the overall African results and the key sub-regional insights derived from the priority gap analysis.

Table 16: Overall Synthesis for continent-wide and sub-regional findings

Region	Overall Priority Pattern	Critical / High Priority Skill Gaps	Moderate Priority Areas	Key Structural Insight
Africa (Overall)	Mostly **moderate gaps** with one high-priority cluster	Evaluation & Quality Assurance (13.1)	Foundational AI/LLM Engineering (11.7), Governance & Ethics (11.5), MLOps (11.5), Linguistic Expertise (10.8), Applied AI (10.2), Data Engineering (10.0)	The continent shows **growing importance of evaluation capacity**, reflecting the increasing need for model validation, benchmarking, and responsible AI systems.
Central Africa	**System-wide high-priority gaps** across all clusters	Data Engineering (16), Evaluation (15), MLOps (15), Foundational AI (12), Linguistic (12), Applied AI (12), Governance (12)	None	Indicates **severe capability scarcity**, with strong projected demand growth but very limited talent availability and geographic distribution.
East Africa	Mixed pattern with	Evaluation & Quality Assurance (20.3),	Foundational AI (10.5),	The region demonstrates **rapid ecosystem expansion**,

Region	Overall Priority Pattern	Critical / High Priority Skill Gaps	Moderate Priority Areas	Key Structural Insight
	one critical gap	Applied AI (15.8), Data Engineering (14), Linguistic Expertise (12)	Governance (10.5), MLOps (10)	but quality assurance and deployment capabilities are struggling to keep pace with growth.
North Africa	**Relatively balanced ecosystem**	None	All clusters moderate (7.9–10.6)	Reflects **more mature AI ecosystems**, where talent supply and demand are relatively aligned across most skill areas.
Southern Africa	**Lowest structural gaps**	None	Data Engineering (10), Governance (10), Applied AI (8), MLOps (8)	Indicates **high talent availability and strong research infrastructure**, particularly around South Africa's established AI institutions.
West Africa	Multiple **high-priority operational gaps**	Data Engineering (14), Linguistic Expertise (14), Evaluation (14), Applied AI (14), Governance (14), MLOps (14)	Foundational AI (10)	Despite **dominance in open-source AI repositories**, capability depth and geographic distribution remain limited.

- The synthesis highlights a **clear regional differentiation in Africa's AI talent ecosystem**. Central Africa exhibits the most severe structural shortages, with high-priority gaps across every skill cluster. East Africa demonstrates strong ecosystem expansion but faces a **critical shortage in evaluation and quality assurance capacity**, which is essential for ensuring reliability and safety in deployed AI systems. North Africa appears comparatively balanced, suggesting that existing academic and industrial infrastructure provides a relatively stable supply of skills.

- Southern Africa displays the lowest priority gaps overall, indicating a **mature talent ecosystem supported by established research institutions and innovation hubs**. West Africa, although leading in open-source development activity, still faces high-priority shortages in several operational and deployment-oriented skills due to limited talent distribution across the region.

- Taken together, the results suggest that **Africa's AI talent gaps are not uniform but regionally differentiated**, with some regions requiring foundational capacity building while others require **specialized skills to support scaling and deployment of AI systems**.

CHAPTER 9: PATHWAYS FOR DEVELOPING AI AND LLM TALENT IN AFRICA

A central theme emerging from the GSMA AI/LLM Talent mapping interviews is the **rapid expansion of interest, participation, and institutional engagement in artificial intelligence across Africa**. One of the participants notes that the number of AI community chapters affiliated with the Deep Learning Indaba network increased significantly from **18 countries in 2018 to about 47 countries by 2025**, reflecting a sharp growth in the ecosystem. As one participant emphasises (00:08:45), *"we started with about 18 countries… that evolved to 27… and then 2023 we had 36 countries and then 2024–2025 we maintain the numbers at 46 and 47 respectively."* This expansion illustrates the growing demand for AI knowledge sharing, research collaboration, and professional networking across the continent.

The increasing participation in conferences also reinforces this trend, with attendance rising from **around 200 participants in 2017 to over a thousand in recent events**. The participant attributes this expansion partly to the **emergence of generative AI technologies and the increasing availability of specialised academic programmes**. As highlighted in the discussion (00:13:01), *"there's much more focus in those particular areas… institutions are recalibrating… now there are undergraduate and postgraduate degrees in data science and artificial intelligence."* This suggests that the surge in AI interest is driven not only by technological innovation but also by institutional responses in higher education systems. Overall, the evidence indicates that the African AI ecosystem is transitioning from a niche research area into a rapidly expanding field characterised by growing communities, educational pathways, and institutional engagement.

Arising from the foregoing, the rapid expansion of artificial intelligence (AI) and large language model (LLM) technologies has intensified the need for effective talent development systems capable of producing skilled professionals who can design, deploy, and manage AI solutions. Across Africa, the growth of AI ecosystems—reflected in increasing research output, expanding open-source development communities, and rising industry demand for AI expertise—has placed significant pressure on existing training pathways. As organisations, governments, and educational institutions seek to strengthen the continent's

AI workforce, understanding the effectiveness of different talent development pathways has become a critical policy and strategic priority.

This chapter examines the pathways through which AI and LLM talent is currently developed across the African continent. These pathways span both **Africa-based mechanisms**, such as universities, research laboratories, innovation hubs, industry apprenticeships, project-based learning programmes, corporate training academies, and government or donor-funded initiatives, as well as **global or online learning channels**, including international certification programmes, online learning platforms, remote internships, global fellowships, and participation in open-source communities. Together, these pathways form a multi-layered ecosystem through which individuals acquire technical knowledge, practical experience, and professional exposure to the global AI landscape.

Beyond mapping the availability of these pathways, the chapter also explores their perceived effectiveness in producing job-ready AI professionals within different African subregions. The analysis recognises that talent development systems are shaped by local institutional capacity, the maturity of national digital ecosystems, and the extent of collaboration between academia, industry, and innovation networks. As a result, the effectiveness of various training pathways may differ significantly across regions and countries, reflecting broader structural differences in infrastructure, research capacity, and industry demand.

In addition to evaluating formal and informal training channels, the chapter examines how organisations across the continent support **AI workforce upskilling** through internal programmes such as technical training, mentorship, innovation challenges, professional certifications, and partnerships with academic institutions. These organisational initiatives represent an increasingly important component of Africa's AI talent pipeline, particularly as firms seek to rapidly upgrade the capabilities of existing staff in response to evolving technological demands.

The chapter also investigates the **pathways that are perceived to produce job-ready AI professionals most rapidly**, highlighting the role of experiential learning approaches such as apprenticeships, project-based development, and hybrid training models that combine academic instruction with practical industry exposure. Finally, the analysis considers the key

structural barriers that limit the effectiveness of AI talent development pathways across the continent, including institutional, financial, and ecosystem-level constraints that may slow the translation of training into employable skills.

By examining both the **structure and performance of AI talent development pathways**, this chapter provides critical insight into how Africa can strengthen its capacity to produce the skilled workforce required to support a growing AI economy. The findings contribute to a deeper understanding of how education systems, innovation ecosystems, and industry partnerships can be better aligned to accelerate the development of AI capabilities across the continent.

9.1 AI/LLM Upskilling Programmes in Africa

The distribution shows that **in-house technical training and short courses or bootcamps are the most prevalent AI upskilling approaches**, each accounting for **19% of all programme mentions**. These training formats are typically easier for organisations to implement and allow rapid skill development in areas such as machine learning engineering, LLM development, and applied AI deployment.

Hackathons and innovation challenges (14.3%) represent another important mechanism for skill development, reflecting the ecosystem's emphasis on practical problem-solving and collaborative innovation. **Mentorship and coaching programmes (11.9%)** also play a significant role, indicating that many organisations rely on experienced practitioners to guide junior AI professionals and accelerate knowledge transfer.

Programmes that involve more structured learning pathways appear somewhat less common. **Research fellowships or internships (9.5%)** and **online learning subscriptions (9.5%)** still feature prominently, suggesting that organisations combine experiential learning with self-paced digital education platforms. Meanwhile, **staff certification programmes (7.1%)** and **industry–university partnerships (7.1%)** highlight the role of formal credentialing and collaboration with academic institutions in strengthening AI talent pipelines.

Finally, **sponsored postgraduate studies (2.4%)** appear to be relatively rare, indicating that only a small number of organisations currently invest in long-term academic training such as MSc or PhD programmes in AI-related fields. Overall, the pattern suggests that organisations across the African AI ecosystem tend to prioritise **short-cycle, practice-oriented training mechanisms** that can rapidly upgrade workforce capabilities in response to evolving technological demands.

9.2 Effectiveness of Africa-based pathways for developing AI/LLM talent

Figure 29 shows the perceived effectiveness of Africa-based pathways for developing AI/LLM talent. The results provide important insights into the perceived effectiveness of Africa-based pathways for developing AI and large language model (LLM) talent across the continent.

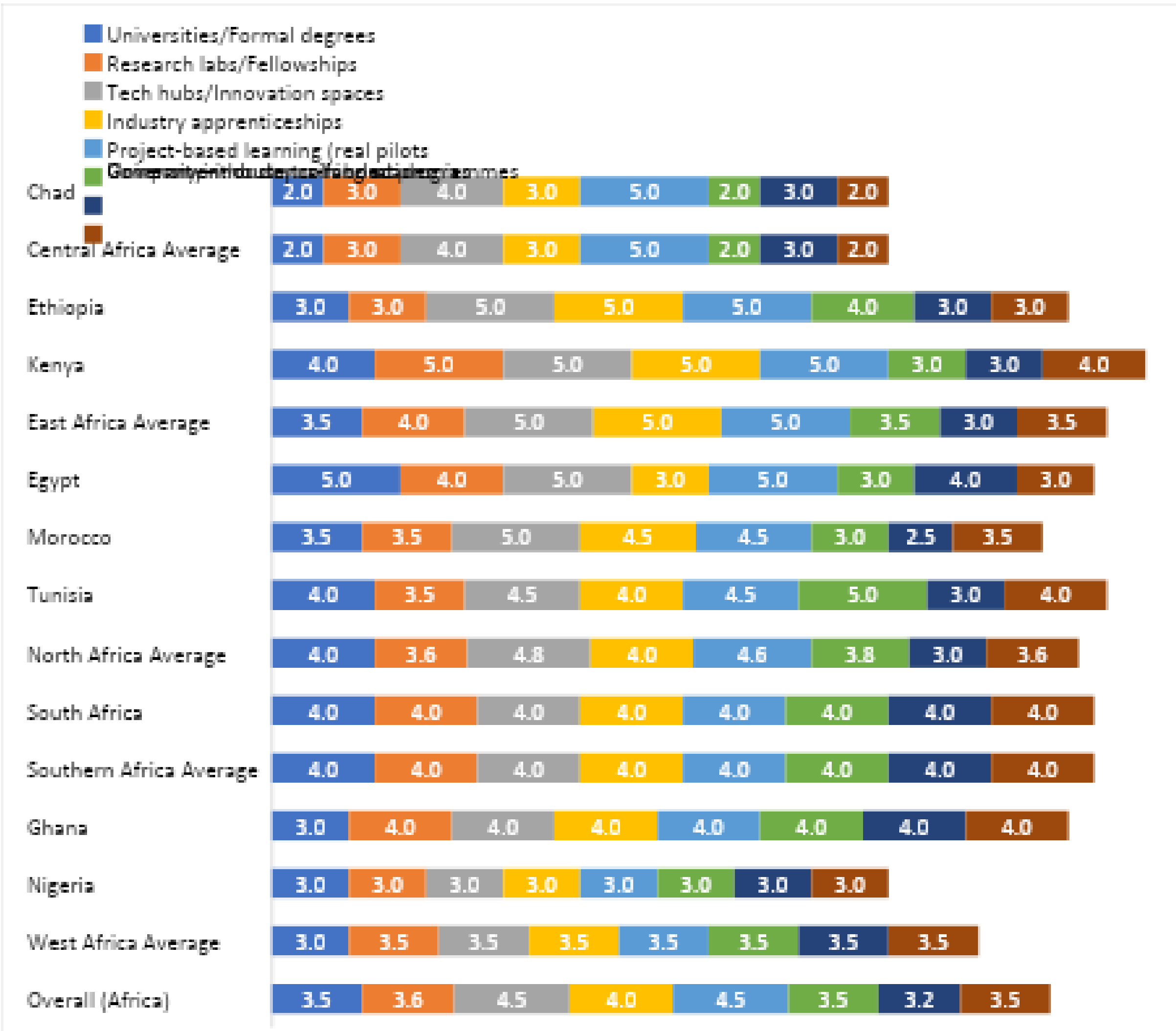


Figure 29: Effectiveness of Africa-based pathways for developing AI/LLM talent

The overall African averages indicate that **tech hubs/innovation spaces and project-based learning through real pilots emerge as the most effective pathways**, each scoring **4.5 out of 5**. These high scores suggest that practical, ecosystem-driven learning environments are particularly effective in equipping individuals with applied AI capabilities. Such environments typically expose learners to real-world problem solving, collaborative experimentation, and industry-relevant tools, which are essential for translating theoretical knowledge into deployable AI solutions.

Industry apprenticeships also receive a relatively strong continental effectiveness rating of **4.0**, highlighting the importance of structured workplace learning in preparing AI professionals. Apprenticeships provide direct exposure to operational AI systems, development workflows, and production environments, enabling learners to acquire hands-on experience that aligns closely with labour market expectations. In contrast, **universities and formal degree programmes receive a moderate effectiveness score of 3.5**, suggesting that while academic institutions play an essential role in building foundational knowledge in computer science, mathematics, and data science, they may not always deliver the practical skills required for immediate workforce readiness.

Similarly, **research labs and fellowships record an average effectiveness score of 3.6**, indicating their importance in advancing specialised knowledge and innovation capacity. However, these pathways tend to serve a smaller subset of highly specialised researchers rather than the broader AI workforce. **Company in-house training academies** also score **3.5**, reflecting the growing role of organisations in internally developing AI talent to address rapidly evolving technological needs. Meanwhile, **government or donor-funded programmes receive the lowest continental rating at 3.2**, suggesting that while such initiatives contribute to capacity building, their overall impact may be limited by funding constraints, implementation gaps, or insufficient integration with industry needs.

A closer examination of **regional patterns** reveals notable differences in the effectiveness of talent development pathways across Africa. In **East Africa**, the average scores are particularly high for **tech hubs, industry apprenticeships, and project-based learning**, all rated at **5.0**, indicating a highly practice-oriented talent development ecosystem. Countries such as Kenya and Ethiopia benefit from vibrant innovation ecosystems, active technology hubs, and strong collaborations between startups and digital development programmes. These conditions appear to create favourable environments for experiential learning and rapid skill acquisition.

North Africa also demonstrates strong pathway effectiveness, particularly in **universities, innovation hubs, and project-based learning**, which score between **4.0 and 4.8**. Countries such as Egypt, Morocco, and Tunisia possess relatively mature higher education systems and growing AI research communities, which support structured learning pathways alongside practical innovation ecosystems. This combination allows North Africa to maintain a balanced talent development structure that integrates academic training with applied learning opportunities.

In **Southern Africa**, the results are remarkably uniform, with all pathways scoring **4.0** on average. This suggests a relatively balanced and mature ecosystem in which universities, industry programmes, government initiatives, and innovation spaces contribute evenly to talent development. The presence of well-established research institutions, technology companies, and policy frameworks in countries such as South Africa likely supports this integrated approach to AI capacity building.

By contrast, **West Africa records more moderate effectiveness levels**, with most pathways averaging around **3.5**. While innovation hubs, apprenticeships, and in-house training programmes remain important contributors, the region's overall effectiveness appears slightly constrained compared to East and North Africa. This pattern may reflect structural challenges such as limited research infrastructure, uneven access to advanced computing resources, and weaker institutional collaboration between universities and industry.

The results are particularly striking in **Central Africa**, where formal universities and company training academies receive relatively low effectiveness scores of **2.0**, while **project-based learning scores a maximum of 5.0**. This contrast suggests that practical, project-oriented learning may be compensating for weaker formal training infrastructure in the region. Innovation hubs also perform relatively well with a score of **4.0**, indicating that emerging innovation ecosystems may play an important role in strengthening AI skills development where institutional capacity remains limited.

Overall, the findings highlight a clear pattern across Africa: **practice-oriented pathways—such as innovation hubs, apprenticeships, and project-based learning—are consistently perceived as more effective than traditional academic or government-led programmes in producing AI-ready talent**. This suggests that strengthening experiential learning environments, industry collaboration, and innovation ecosystems may be one of the most effective strategies for accelerating AI workforce development across the continent.

9.3 Effectiveness of Global/Online Pathways for African AI talent

The assessment of **global and online pathways for developing African AI and LLM talent** reveals that international learning ecosystems play a significant role in strengthening the continent's AI capacity. Across Africa, these pathways generally receive relatively high effectiveness scores, reflecting the importance of global knowledge networks, digital learning platforms, and remote collaboration opportunities in bridging gaps in local training infrastructure. Figure 30 shows the perceived effectiveness of Global/Online Pathways for African AI talent.

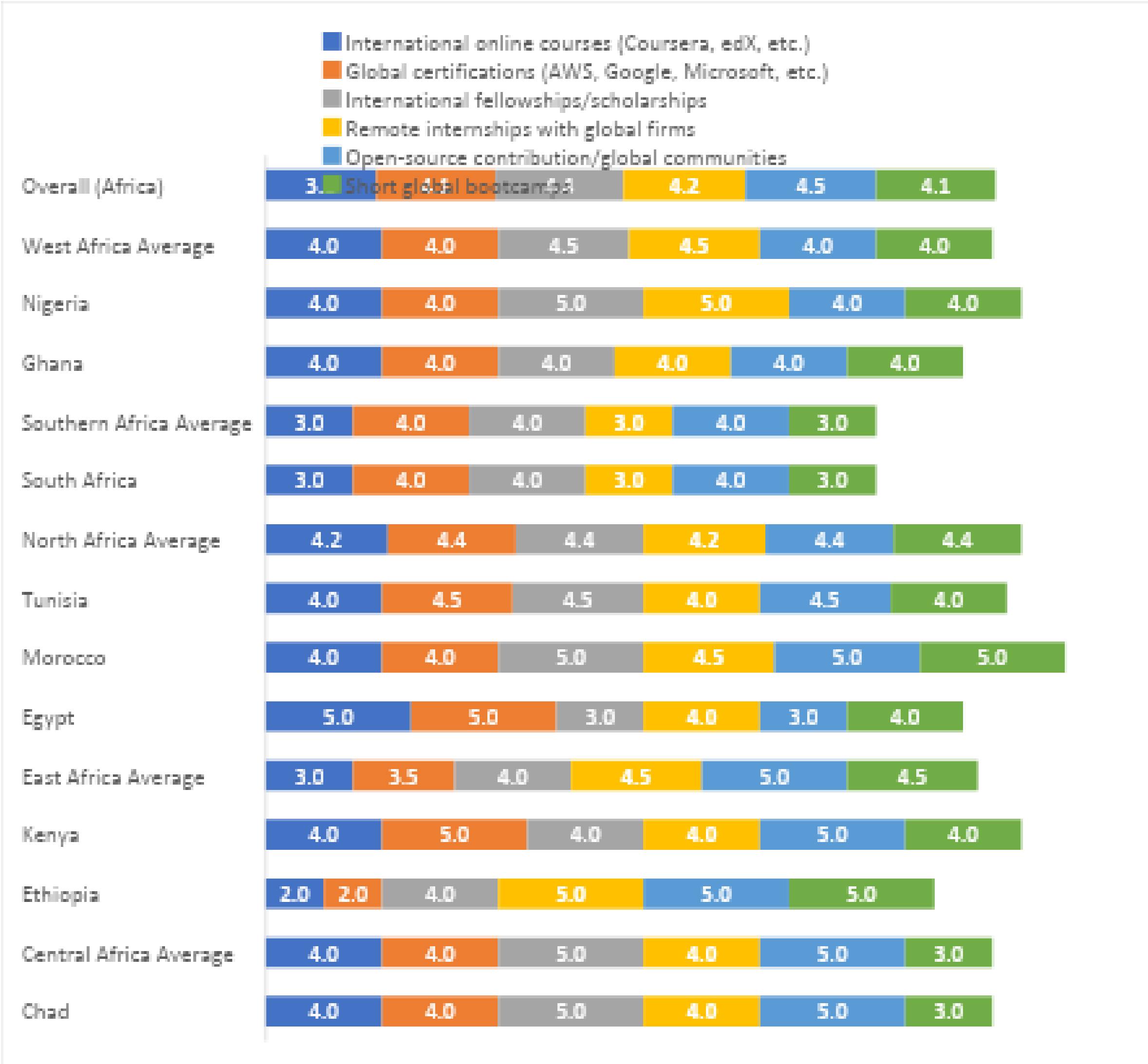


Figure 30: Effectiveness of Global/Online Pathways for African AI talent

The continental averages indicate that **open-source contribution and participation in global developer communities emerge as the most effective pathway**, with an average score of **4.5**, followed by **international fellowships and scholarships (4.4)**, **remote internships with global firms (4.2)**, **global certifications (4.1)**, **short global bootcamps (4.1)**, and **international online courses (3.8)**. This distribution highlights the growing integration of African AI professionals into international digital ecosystems where knowledge exchange, collaborative development, and practical exposure to real-world AI systems are readily accessible.

The strong performance of **open-source communities** reflects the critical role that platforms such as GitHub play in enabling African developers to collaborate with global teams, access cutting-edge AI tools, and contribute to widely used machine learning frameworks. Through open-source participation, developers gain practical experience in software engineering practices, code review processes, and large-scale collaborative development, which significantly enhances their technical credibility and employability. Similarly, **international fellowships and scholarships** receive high effectiveness ratings because they provide structured opportunities for African professionals to access advanced research environments, specialised training, and mentorship within leading global institutions.

Remote internships with global firms also receive a strong continental score, demonstrating the increasing importance of distributed work models in the AI labour market. Remote internships allow African developers to gain hands-on experience working on production-level AI systems without the need for physical relocation, thereby lowering barriers to entry into global technology ecosystems. These opportunities also facilitate knowledge transfer, exposure to international engineering standards, and integration into global professional networks.

Global certifications, such as those offered by major technology providers, also contribute meaningfully to AI talent development. These certifications help professionals validate their technical competencies in areas such as cloud computing, machine learning deployment, and data engineering. While certification programmes may not fully substitute for hands-on experience, they provide widely recognised credentials that can improve employability in both local and international labour markets.

Short global bootcamps also receive strong ratings, reflecting their emphasis on intensive, practice-oriented training. These programmes typically focus on rapid skill acquisition in areas such as machine learning engineering, data science, and generative AI development. Because bootcamps are often designed in partnership with industry practitioners, they tend to prioritise practical applications and real-world problem solving, making them effective complements to traditional academic education.

At the **regional level**, the perceived effectiveness of global pathways varies across Africa. **North Africa records the strongest overall performance**, with regional averages exceeding **4.2 across most pathways**. This suggests that North African professionals may have relatively strong access to global learning opportunities and international collaboration networks. The region's linguistic proximity to European research and technology ecosystems, as well as established academic partnerships with institutions abroad, may contribute to this strong engagement with global talent development pathways.

West Africa also demonstrates relatively strong effectiveness scores, particularly for **international fellowships and remote internships**, both averaging **4.5**. Countries such as Nigeria and Ghana increasingly participate in global digital labour markets, and many professionals in the region leverage remote opportunities, online learning platforms, and international scholarships to enhance their technical capabilities. These global connections appear to play an important role in compensating for local infrastructure constraints.

In **East Africa**, global pathways are particularly effective for **remote internships and open-source collaboration**, with strong average scores of **4.5 and 5.0 respectively**. This reflects the region's vibrant developer communities and the strong culture of participation in global open-source ecosystems. Countries such as Kenya have established reputations as technology innovation hubs, which likely encourages greater participation in global collaborative projects and remote work opportunities.

By contrast, **Southern Africa records slightly lower effectiveness ratings for several global pathways**, particularly **remote internships and short global bootcamps**, both averaging **3.0**. This may reflect the region's relatively stronger domestic training infrastructure, meaning that local universities, research institutions, and company training programmes already provide substantial learning opportunities, reducing reliance on external pathways.

In **Central Africa**, the results highlight a particularly strong reliance on **international fellowships and open-source communities**, both scoring **5.0**. These pathways may provide critical alternatives where domestic training infrastructure remains limited. International programmes and online collaborative networks therefore appear to play a vital role in expanding access to advanced AI knowledge and professional opportunities in the region.

Overall, the findings indicate that **global and online pathways are an essential complement to domestic talent development systems across Africa**. While local universities, innovation hubs, and industry programmes remain important, international learning platforms, fellowships, remote work opportunities, and open-source communities significantly expand the continent's AI learning ecosystem. These global connections not only accelerate skill acquisition but also integrate African AI professionals into the broader international technology landscape, thereby strengthening both individual career pathways and the continent's overall AI innovation capacity.

9.4 Pathways that Produce most Job-Ready AI/LLM Professionals

Respondents were asked to identify which pathway they believe produces **job-ready AI/LLM professionals most rapidly within their regional ecosystems**. The responses indicate a strong preference for **hybrid learning models**, complemented by a smaller but significant emphasis on **apprenticeship or project-based learning pathways**.

A frequency analysis of the responses shows that **hybrid pathways**—defined as a combination of multiple training mechanisms such as formal education, practical projects, industry exposure, and online learning—were selected by **8 out of the 11 respondents**, representing **72.7%** of the responses. In contrast, **apprenticeship or project-based learning models** were identified by **3 respondents**, accounting for **27.3%** of the responses.

The dominance of the **hybrid model** suggests that stakeholders across the African AI ecosystem recognise that no single training pathway is sufficient to prepare professionals for the complex demands of AI and LLM development. Instead, effective talent development appears to rely on **integrated learning systems** that combine theoretical knowledge, practical implementation, industry engagement, and continuous skills development. Hybrid pathways often involve a mix of university training, online courses, industry certifications, hands-on projects, mentorship, and participation in innovation ecosystems such as technology hubs and developer communities. This blended approach allows learners to simultaneously build foundational knowledge and applied technical skills.

The responses also highlight the importance of **apprenticeship and project-based learning**, which were selected by more than one-quarter of respondents. These pathways emphasise **hands-on experience through real-world problem solving**, allowing learners to work directly on applied AI projects, prototypes, or production systems. Such experiential learning models are particularly valuable in AI development, where practical exposure to data pipelines, model training, deployment environments, and system optimisation is essential for building job-ready competencies.

At country-level, the interview data also identifies the **dominant pathways through which AI talent currently develops technical skills in Egypt**. One of the participants emphasises (00:12:40) that the most common entry point into AI learning is through **online courses and digital learning platforms**, which provide accessible training resources for aspiring developers. These platforms allow individuals to learn machine learning concepts, programming languages, and AI frameworks independently.

The second major pathway highlighted in the interview is **on-the-job learning through internships or practical work experience**. According to the participant (00:12:55), internships allow graduates to acquire the practical experience required to transition from theoretical learning to professional employment. This combination of online education and workplace training forms the **core talent development pipeline** in the Egyptian AI ecosystem. The emphasis on practical experience suggests that theoretical education alone is insufficient to prepare graduates for industry roles.

Overall, the results suggest that the **fastest pathway to developing job-ready AI professionals in Africa lies in combining structured learning with practical industry experience**. Hybrid models provide the flexibility to integrate multiple learning environments, while apprenticeship and project-based approaches ensure that learners gain the real-world skills required to design, deploy, and maintain AI systems in production settings. Together, these pathways highlight the importance of **practice-oriented, ecosystem-based talent development strategies** for accelerating the growth of Africa's AI workforce.

The interview insights further highlight the **importance of combining multiple learning approaches to develop job-ready AI professionals**. The participant describes an ideal training model that integrates formal education, industry engagement, peer learning, and experimental practice environments. As emphasised during the discussion (00:56:07), *"the* *hybrid approach includes curriculum, environment, and physical location… balancing online and in-person learning."* This hybrid model is particularly important because AI skills require both theoretical understanding and practical application. The participant suggests that learning environments should combine **cloud-based experimentation with hands-on engagement with physical computing infrastructure**, ensuring that students understand both conceptual and operational aspects of AI systems. Additionally, the participant highlights the role of **peer-to-peer learning and safe experimentation environments**, where individuals can test ideas through pilots or sandbox projects without the risk of damaging operational systems.

Another key aspect of hybrid learning is **collaboration between universities and industry professionals**, which helps bridge the gap between academic training and labour market expectations. As noted by one of the interview participants (00:58:29), *"bringing industry professionals into academic settings helps students understand the practical reality of the field."* This demonstrates that developing AI talent requires a multidimensional training ecosystem that integrates education, experimentation, and industry exposure.

9.5 Barriers to Effective AI Talent Pathways in Africa

Respondents were asked to identify the **single most significant barrier limiting the effectiveness of AI and LLM talent development pathways within their regions**. The responses reveal that structural ecosystem constraints—particularly weak institutional linkages and financial limitations—remain the most significant challenges affecting the development of AI talent across the continent.

1) Weak Industry–Academia Links

A frequency analysis of the responses shows that **weak industry–academia links** emerged as the most frequently cited barrier, appearing in **5 out of the 11 responses**, representing **45.5%** of all responses. This suggests that the limited collaboration between universities and industry actors remains a major constraint to effective AI talent development. When academic training programmes are not closely aligned with industry needs, graduates may lack exposure to real-world AI development environments, production systems, and practical problem-solving experiences. As a result, the transition from academic learning to employment can become more difficult.

2) Limited Funding for Learners

The second most frequently identified barrier is **limited funding for learners**, which was cited in **4 responses**, accounting for **36.4%** of the responses. Financial constraints can affect access to specialised AI education, certification programmes, research opportunities, and advanced training. Many high-quality AI training opportunities—such as specialised courses, certifications, or postgraduate programmes—often require significant financial investment, which may limit participation for many aspiring AI professionals across the continent.

3) Brain Drain or Talent Migration

A closely related theme concerns the **migration of skilled AI professionals from Africa to global institutions**, commonly described as brain drain. **Brain drain or talent migration** was identified in **1 response (9.1%)**, highlighting the challenge of retaining highly skilled AI professionals within local ecosystems. As global demand for AI expertise continues to grow, many talented individuals may seek opportunities abroad or work remotely for international firms, potentially reducing the availability of experienced professionals within domestic markets.

Empirical evidence from the interviews reveal that international universities and technology firms actively recruit African researchers through competitive funding opportunities, particularly doctoral scholarships and postdoctoral positions. As the participant emphasises (00:29:46), *"the European and the Americas are stealing our talent… offering these lucrative PhD positions and taking them out of Africa."* The interview also highlights broader socioeconomic drivers of migration, including employment limitations and political or personal considerations. According to the participant (00:31:06), talent mobility is influenced by factors such as **political environments, personal freedom, and financial incentives provided by international institutions**.

Additionally, the discussion points to structural labour market challenges, noting that **around 40% of educated youth in South Africa may experience unemployment**, which further encourages outward migration. These dynamics illustrate that brain drain is not simply a loss of talent but reflects **structural imbalances between global research ecosystems**. Without adequate domestic research funding, industry demand, and career pathways, African AI professionals may continue seeking opportunities abroad. Addressing this issue therefore requires strengthening local research ecosystems and innovation infrastructures.

At the same time, the interview highlights a **brain drain of experienced AI professionals**, who often relocate or work remotely for companies in Europe or the Gulf region where salaries are significantly higher. Another interview participant emphasises (00:11:20) that local companies must compete with international salary levels, making it difficult to retain senior talent. Consequently, the ecosystem experiences **an oversupply of junior talent alongside a shortage of experienced professionals**. This imbalance affects the growth of local AI companies because senior engineers and technical leaders are essential for scaling advanced projects. Overall, the findings suggest that **talent retention and experience development represent critical challenges for the Egyptian AI labour market**.

4) Lack of Real-World Projects

Similarly, **lack of real-world projects** was also cited in **1 response (9.1%)**. The absence of practical, industry-based projects can limit the opportunities for learners to apply theoretical knowledge to real-world AI development tasks. Without exposure to applied problem-solving environments—such as production datasets, operational systems, or industry use cases—learners may struggle to develop the hands-on competencies required by employers.

Overall, the results suggest that **institutional coordination and financial accessibility are the most significant systemic barriers to AI talent development in Africa**. Strengthening collaboration between universities and industry actors, expanding funding opportunities for learners, and increasing access to real-world project environments may therefore play a critical role in improving the effectiveness of AI talent development pathways across the continent.

5) Untapped Talent Potential and Structural Barriers to Talent Utilisation

The interview strongly emphasises that **Africa possesses substantial AI talent that remains under-recognised or underutilised due to structural limitations**. One participant explicitly states that talent is not the primary constraint but rather the ecosystem conditions that enable talent to flourish. As the participant notes (00:27:09), *"we do have talent, a lot of talent… some of it is tapped into… and some of it others don't know that it exists."* The discussion highlights how many talented developers and researchers participate in conferences or innovation showcases but lack the resources to scale their projects afterwards. As explained (00:28:32), *"they come and do a showcase but nobody knows about them… either because they cannot expand further or they don't have the resources."* This indicates that **ecosystem support structures such as funding, infrastructure, and industry partnerships remain insufficient** to convert talent into scalable innovation.

Furthermore, the participant notes that Africa's intellectual capacity is significant but often constrained by limited financial resources. At one point the participant remarks (00:17:03), *"Africa has a lot of intellectual capacity that is untapped… we don't necessarily have the financial resources but we have resources in other ways."* This observation highlights the contrast between **human potential and structural constraints**, suggesting that investment and institutional support could significantly expand Africa's AI capabilities.

6) Governance, Policy Development, and Regulatory Challenges

The interview also identifies **AI governance and policy development as a critical but complex issue across Africa**. While several countries have begun developing national AI strategies, the pace of policy formulation varies widely. As the participant notes (00:22:26), countries such as **Kenya, Madagascar, and Tunisia had already initiated AI policy frameworks by 2023**, while others are still developing regulatory approaches.

In South Africa, the participant describes a particularly complex policy environment shaped by extensive legal frameworks and democratic consultation processes. For example, the **Protection of Personal Information Act (PoPIA)** imposes strict data governance rules that can complicate AI research by limiting access to datasets or allowing individuals to withdraw consent from research samples. As explained (00:44:04), such regulations may reduce dataset reliability and affect research outcomes.

Despite these challenges, the participant emphasises that governance frameworks are essential to prevent harmful applications of AI technologies, including military misuse or unethical surveillance. This theme therefore highlights the need for **balanced regulatory frameworks that support innovation while ensuring responsible AI deployment**.

7) Knowledge Visibility and Documentation Challenges

A final theme emerging from the interview concerns the **lack of visibility and documentation of AI expertise within Africa**. The participant explains that much of the knowledge and experimentation taking place across the continent is not formally published or documented in globally recognised formats. As highlighted (01:18:55), the participant notes that African knowledge systems often remain *"tacit rather than explicit,"* meaning that expertise exists but is not easily discoverable in academic or digital repositories. This invisibility creates the impression that certain technical capabilities—such as MLOps or evaluation frameworks—are absent in Africa, when in reality they may simply be undocumented or shared informally within communities.

Additionally, the participant suggests that some organisations intentionally restrict access to their datasets or processes for competitive reasons, further limiting public visibility. The theme underscores the importance of **improving documentation, open data practices, and knowledge dissemination** to ensure that African innovations are recognised and integrated into global AI research networks.

8) The Challenge of Language Models with African Context

The interviews insights detailed how existing AI models have limited understanding of African languages due to restricted datasets, which poses a barrier to large populations who do not speak priority languages like English or French. They provided an example of a language model performing a direct, nonsensical translation of an African idiom, demonstrating that the models fail to grasp cultural context, proverbs, and names (01:08:06). They explained that the African NLP community is working to create culturally accurate datasets and establish meaningful definitions for concepts like "artificial intelligence" in various African languages (01:10:33).

9) Infrastructure Constraints as a Foundational Barrier to AI Deployment

A dominant theme emerging from the interview is that insufficient computing and cloud infrastructure represents one of the most significant barriers to AI adoption and deployment in Egypt and similar African markets. One of the participants emphasises (00:02:20) that although there is growing demand for AI applications across sectors such as banking, government, healthcare, and insurance, *"the main barrier for this is the lack of infrastructure… we don't have any type of local cloud here in Egypt."* This limitation is particularly problematic in high-sensitivity sectors where data must remain on-premise and cannot be transferred to foreign cloud regions due to regulatory or security concerns. As a result, organizations are required to invest in local GPU clusters and smaller internal computing environments to run AI applications, which significantly raises the cost of adoption.

The interviewee also highlights that building national-level AI infrastructure requires strategic public investment similar to traditional infrastructure such as transportation, healthcare, or education. One of the participants emphasises (00:03:35) that neighbouring Gulf countries succeeded in attracting hyperscale data centres through large investments and partnerships with global technology companies. However, many African economies lack the financial capacity to pursue similar projects, which slows the development of domestic AI ecosystems. The implication is that **without large-scale infrastructure investments, AI adoption will remain limited to organisations that can afford private computing environments**. Overall, this theme underscores that digital infrastructure forms the foundational layer of the AI ecosystem, and its absence significantly constrains the scaling of AI solutions.

Overall, the findings reveal that Africa's AI ecosystem is characterised by **rapid growth in interest, significant untapped talent, and a strong emphasis on developing context-specific AI solutions**. However, this potential is moderated by several structural challenges, including **brain drain, limited resources for scaling innovation, regulatory complexity, and the**

under-documentation of local expertise. At the same time, the findings highlight promising developments such as **hybrid learning pathways, expanding AI communities, and emerging policy frameworks**, which collectively point toward a maturing and increasingly coordinated AI ecosystem across the Africa continent.

9.6 The Need for African-Centric AI and Localised Solutions

A major theme from the interviews borders on the **importance of developing AI systems that reflect African cultural, linguistic, and socioeconomic contexts**. The interview highlights concerns that many existing global AI models fail to adequately represent African realities. One participant stresses that African stakeholders are increasingly questioning whether imported technologies are suitable for local contexts. As noted during the discussion (00:14:11), *"in our particular context as Africa firstly do we want artificial intelligence in the form that is being presented to us… how can we create our own version that works within the African context."*

This issue is particularly visible in the domain of natural language processing, where existing models often lack sufficient training data for African languages. The participant explains that language models frequently misinterpret idioms and culturally specific expressions due to limited datasets. As highlighted (01:08:06), the participant notes that models sometimes produce *"direct, nonsensical translations of African idioms"* because they lack contextual understanding of cultural expressions. The African AI research community is therefore increasingly focused on **developing culturally relevant datasets, linguistic resources, and evaluation frameworks** to improve representation. The emphasis on African-centric AI reflects a broader strategic orientation toward **technology sovereignty and contextual innovation**. Rather than merely adopting external AI systems, African researchers aim to adapt or redesign these systems to support local economies, languages, and governance priorities. This theme underscores the importance of contextualisation as a core principle for AI development on the continent.

Developers should build AI solutions for global markets

A key theme emerging from the interview concerns the **strategic opportunity for African developers to build AI solutions for global markets**. One of the participants emphasises (00:15:45) that African companies should not limit themselves to solving local problems but should also build products that can compete internationally. The participant explains that *"we can build from Africa for the global market."* This perspective challenges the assumption that African AI innovation must be confined to local applications.

Developing solutions tailored to African contexts

At the same time, the participant stresses the importance of **developing solutions tailored to African contexts**, particularly in areas where local knowledge and datasets provide a competitive advantage. According to the discussion (00:16:10), building solutions that leverage African data and address African challenges could enable local companies to outperform external technology providers attempting to operate in the region. The combination of **global ambition and local relevance** therefore represents a promising strategy for the African AI ecosystem. Ultimately, this finding suggests that Africa's long-term success in AI may depend on its ability to **leverage local insights while participating in global technology markets**.

CHAPTER 10: CONCLUSIONS AND RECOMMENDATIONS

10.1 Key Takeaways

10.1.1 Summary of the AI Skills Landscape

- The findings across This research reveal that Africa's AI ecosystem is expanding rapidly but remains structurally uneven across regions, countries, and skill clusters. Evidence from **AI job postings, research publications, and open-source developer activity** shows that AI development across the continent is characterised by **strong demand signals, emerging knowledge production, and rapidly growing developer ecosystems**, though these elements remain unevenly distributed.

- Analysis of **AI labour market demand** indicates that job opportunities are highly concentrated geographically. North Africa leads, followed by West Africa and Southern Africa. At the country level, **South Africa, Morocco, Egypt, Nigeria, and Kenya collectively account for approximately 63% of all AI job demand in Africa**. This demonstrates that AI employment opportunities are concentrated in a small number of national technology hubs.

- In terms of **skills demand**, the labour market prioritises a diverse set of technical competencies. **Foundational AI skills** represent the largest share of job demand, followed by **Data Engineering**, **Applied AI**, **Evaluation**, and **Governance**. Linguistic AI accounts for **11.45%**, while **MLOps represents only 6.26%**, suggesting that infrastructure and deployment expertise remain a smaller but growing segment of the talent market.

- Evidence from **AI research publications** shows a similarly concentrated but rapidly expanding knowledge ecosystem. A small group of countries dominates AI research output, with **Nigeria, Morocco, Ghana, South Africa, and Algeria contributing more than 51% of all publications**. Regionally, **North Africa and West Africa together produce almost 60% of the continent's AI research output**. Research production is strongly concentrated in **Foundational AI and Applied AI**, indicating that African research activity remains focused primarily on technical model development rather than operational deployment or governance.

- Open-source development activity provides a third perspective on AI capability production. Analysis of **GitHub repositories** shows that **West Africa dominates developer-led AI capability production, accounting for 53.14% of repositories**, followed by **North Africa and East Africa**. At the country level, **Ghana, Nigeria, and Egypt together produce over 55% of all repositories**, highlighting strong national concentration within the developer ecosystem.

- Unlike job demand and research production, **GitHub activity is overwhelmingly concentrated in Linguistic AI**, which represents **63.98% of repositories**, reflecting strong engagement with **language technologies, localisation efforts, and generative AI applications**. This indicates that African AI capability development is heavily oriented toward language technologies rather than broad sectoral AI deployment.

- Overall, the AI ecosystem across Africa can be characterised as **geographically concentrated but technically diversified**, with demand signals spread across multiple skill clusters while production capacity remains concentrated in specific regions and countries.

10.1.2 Critical Gaps in Africa's AI Talent Ecosystem

- Despite the rapid growth of AI activity across the continent, the findings reveal several **structural imbalances between AI demand, knowledge production, and capability development**.

- At the **regional level**, there is clear misalignment between where AI jobs exist and where technical capability is being produced. **North Africa accounts for the largest share of job demand (37.25%) but produces only 19.66% of GitHub repositories**, indicating a demand-driven ecosystem that relies on external talent supply. In contrast, **West Africa produces the majority of open-source AI capability (53.14%) but accounts for only 20.61% of job demand**, suggesting that developer capacity is emerging faster than local employment opportunities.

- Country-level analysis reveals similar structural imbalances. **South Africa and Morocco exhibit strong labour market demand but comparatively low open-source production**, while **Ghana shows a major over-concentration of GitHub capability relative to job demand**. In contrast, **Nigeria demonstrates the strongest alignment between demand, research production, and developer activity**, indicating a relatively balanced AI ecosystem.

- Skill cluster analysis further highlights structural gaps in the continent's AI capability base. While **Foundational AI demonstrates strong alignment across demand, research, and GitHub production**, several other clusters are significantly underdeveloped. **Evaluation and Quality Assurance**, **Governance**, and **MLOps** are particularly underrepresented relative to labour market demand. For example, **Evaluation skills account for 14.16% of job demand but only 0.63% of GitHub repositories**, while **Governance represents 13.53% of demand but just 0.29% of repositories**. These gaps indicate that Africa's AI ecosystem is still heavily focused on model development rather than responsible deployment and lifecycle management.

- The **AI talent priority gap analysis** reinforces these findings. At the continental level, **Evaluation and Quality Assurance emerges as the only high-priority gap**, reflecting the growing importance of model validation, benchmarking, and responsible AI governance as AI systems become more widely deployed. Other skill clusters—including **Foundational AI, Governance, MLOps, Linguistic expertise, Applied AI, and Data Engineering—show moderate priority gaps**, indicating that supply remains insufficient relative to projected demand growth.

- Regional analyses reveal different structural dynamics across Africa. **Central Africa exhibits system-wide high-priority gaps across all skill clusters**, indicating severe talent scarcity and limited ecosystem maturity. **East Africa shows a critical gap in Evaluation and Quality Assurance**, reflecting the rapid expansion of AI initiatives without sufficient quality assurance capacity. In contrast, **North Africa and Southern Africa display relatively balanced ecosystems**, suggesting stronger institutional capacity and more mature AI infrastructure.

- These findings demonstrate that Africa's AI ecosystem faces **not only talent shortages but also structural mismatches between different parts of the innovation system**, particularly between research production, developer activity, and labour market demand.

10.1.3 Feasibility of AI Talent Development Pathways

- The research also examined the **effectiveness of different pathways for developing AI and LLM talent in Africa**, including both **Africa-based pathways and global or online learning pathways**.

- Survey findings indicate that **practice-oriented learning environments are perceived as the most effective mechanisms for developing AI talent within Africa**. Across regions, **project-based learning environments, technology hubs, and industry apprenticeships received the highest effectiveness ratings**, often scoring **4–5 on a five-point scale**. These pathways provide learners with opportunities to work on real-world AI projects, develop practical programming skills, and engage with industry practitioners.

- Formal university degrees remain important but are generally perceived as less effective on their own. Respondents consistently indicated that **university programmes require stronger integration with industry projects and innovation ecosystems** to produce job-ready AI professionals.

- Global learning pathways also play a critical role in Africa's AI talent development. **International online courses, global certifications, open-source communities, and remote internships with global firms all received high effectiveness ratings across multiple regions**. In particular, **open-source participation and global AI communities were consistently rated among the most effective pathways**, reflecting the importance of collaborative development platforms such as GitHub for building practical AI skills.

- Survey responses further indicate that **hybrid learning models combining multiple pathways are the most effective strategy for producing job-ready AI professionals**.

The majority of experts identified **hybrid pathways—integrating formal education, project-based learning, online training, and apprenticeships—as the fastest route to developing AI talent in their regions**. This reflects the complex skill requirements of modern AI development, which require both theoretical understanding and extensive hands-on experience.

- However, the effectiveness of these pathways is constrained by several systemic barriers. The most frequently identified constraints include **limited funding for learners, weak industry–university linkages, limited access to real-world AI projects, and ongoing talent migration to global technology markets**. These challenges reduce the ability of local ecosystems to scale AI training programmes and retain highly skilled professionals.
- Overall, the findings suggest that **scaling Africa's AI talent pipeline will require coordinated investment in hybrid training ecosystems**, combining formal education with industry engagement, open-source collaboration, and global learning opportunities.

10.2 Policy Recommendations

The findings of This research demonstrate that Africa's AI ecosystem is expanding rapidly but faces structural imbalances between labour market demand, research production, open-source capability development, and talent development pathways**.** Addressing these imbalances requires coordinated policy interventions that strengthen infrastructure, expand talent development pathways, improve industry–academia collaboration, and support the operationalisation of AI systems across the continent. The following recommendations are grounded in the empirical findings of this report and are designed to be specific, measurable, achievable, relevant, and time-bound**.**

1. Invest in AI Infrastructure and Sovereign Compute Capacity

African governments and regional development institutions should establish **national or regional AI compute infrastructure programmes**, including sovereign cloud platforms and GPU clusters, in at least **ten strategic African AI hubs by 2030**. Interview evidence and ecosystem analysis show that **lack of local cloud infrastructure is a major barrier to AI deployment**, particularly in sectors such as banking, healthcare, and government that require secure on-premise or localised data infrastructure. Furthermore, labour market data indicates that **North Africa accounts for 37.25% of AI job demand**, yet infrastructure capacity across much of the continent remains limited. Without reliable compute infrastructure, local organisations must rely on foreign cloud providers, increasing costs and limiting data sovereignty.

SMART indicators

- Establish **10 regional AI compute centres by 2030**
- Ensure **at least 60% of national government AI projects utilise local infrastructure**
- Provide subsidised GPU access to **at least 5,000 African AI developers annually**
- Strengthening compute infrastructure will enable African organisations to **deploy AI solutions locally, protect sensitive data, and support large-scale AI innovation ecosystems**.

2. Strengthen Industry–Academia Collaboration for AI Skills Development

Governments, universities, and private-sector firms should establish **structured AI industry–academia partnership programmes**, including mandatory **industry internships or applied research placements for at least 50% of AI-related university students by 2028**. Survey findings indicate that **project-based learning environments, apprenticeships, and innovation hubs are the most effective pathways for developing AI talent**, while traditional academic programmes alone are perceived as less effective. Additionally, interview findings highlight that **many graduates possess raw technical skills but lack real-world industry experience**, which reduces employability. The gap between **academic training and industry needs** contributes to the observed mismatch between **AI talent availability and job readiness**, particularly in rapidly evolving areas such as MLOps, evaluation, and applied AI deployment.

SMART indicators

- At least **50% of AI-related students complete industry internships by 2028**
- Establish **AI research–industry collaboration programmes in 100 African universities by 2030**
- Support **200 joint AI research and deployment projects annually**
- Strengthening industry–academia collaboration will help ensure that graduates develop **practical skills aligned with labour market demand**.

3. Expand Practice-Based AI Training Ecosystems

Governments, development agencies, and private sector partners should expand **practice-based AI learning ecosystems**, including technology hubs, accelerators, and project-based training programmes, to train **at least 100,000 AI practitioners across Africa by 2030**. Survey results consistently show that **project-based learning environments and innovation hubs are among the most effective pathways for AI skill development**. These environments allow learners to work on **real-world AI applications**, which significantly improves job readiness. Additionally, GitHub analysis reveals strong growth in **developer-led AI capability production**, particularly in West Africa. Supporting innovation hubs and open-source collaboration platforms will help scale this momentum while improving the **depth and diversity of technical skills** beyond linguistic AI development.

SMART indicators

- Train **100,000 AI practitioners through innovation hubs by 2030**

- Establish **at least one major AI innovation hub in every African sub-region by 2028**
- Support **500 open-source AI projects addressing African challenges**
- Scaling practice-based training ecosystems will strengthen Africa's **applied AI development capacity and entrepreneurial AI ecosystems**.

4. Prioritise Development of Underrepresented AI Skill Clusters

African AI talent development initiatives should prioritise training programmes in **Evaluation and Quality Assurance, MLOps, and AI Governance**, with the goal of increasing training capacity in these fields by **at least 200% by 2030**. The priority gap analysis shows that **Evaluation and Quality Assurance represents the only high-priority gap across the continent**, while **Governance and MLOps are significantly underrepresented in both research and open-source production** relative to labour market demand. For example, Evaluation accounts for **14.16% of job demand but only 0.63% of GitHub repositories**; Governance represents **13.53% of demand but just 0.29% of repositories**; MLOps remains extremely underdeveloped across research and developer ecosystems. Without strengthening these operational skill clusters, Africa risks building AI systems without sufficient **testing, governance, and deployment infrastructure**, which could undermine trust and scalability.

SMART indicators

- Train **20,000 AI professionals in evaluation and AI safety by 2030**
- Establish **MLOps training programmes in at least 50 universities**
- Develop **national AI governance training programmes in 15 African countries**
- Targeted investment in these areas will support the development of **safe, reliable, and scalable AI systems across Africa**.

5. Support Open-Source AI Ecosystems and Developer Communities

African governments and international partners should establish **continental open-source AI development programmes** that provide funding, infrastructure, and mentorship for **at least 10,000 open-source AI contributors by 2030**. GitHub analysis reveals that **developer-driven AI capability production is expanding rapidly**, with repositories increasing from **2 projects in 2009 to 9,598 in 2025**. However, this capability production is heavily concentrated in **linguistic AI (63.98%)**, indicating limited diversification into other important skill clusters such as applied AI, evaluation, and MLOps. Supporting open-source communities will allow developers to collaborate on **shared tools, datasets, and AI infrastructure**, accelerating capability development across the continent.

SMART indicators

- Support **10,000 African open-source AI contributors by 2030**
- Fund **1,000 open-source AI projects addressing African use cases**
- Develop **pan-African AI developer collaboration platforms**
- Expanding open-source ecosystems will strengthen **practical AI capability development and collaborative innovation**.

6. Implement AI Talent Retention and Global Talent Mobility Strategies

African governments should implement **AI talent retention and diaspora engagement programmes**, including remote work platforms, innovation funding, and tax incentives, to retain or reconnect **at least 25% of African AI professionals currently working abroad by 2035**. Interview findings highlight that **brain drain remains a significant challenge**, particularly for experienced AI professionals who relocate to Europe or Gulf countries due to higher salaries and stronger research infrastructure. While the continent produces increasing numbers of graduates and developers, **retaining experienced AI professionals is essential for building mature AI ecosystems**, mentoring junior talent, and scaling AI innovation.

SMART indicators

- Establish **AI diaspora collaboration programmes in 20 African countries**
- Create **remote AI employment programmes connecting African firms with global markets**
- Support **1,000 diaspora-led AI innovation projects by 2035**
- Strengthening talent retention and diaspora engagement will help Africa build **more sustainable and globally competitive AI ecosystems**.

7. Promote AI Solutions for African Societal Challenges

African governments and development organisations should prioritise **AI innovation programmes focused on solving African development challenges**, including agriculture, healthcare, financial inclusion, and education. Interview evidence emphasises that **Africa has a unique opportunity to build AI solutions tailored to local problems**, rather than relying solely on technologies developed in other regions. Leveraging Africa's linguistic diversity, local data, and contextual knowledge can generate AI applications that are more effective in addressing regional challenges. Furthermore, the strong concentration of **linguistic AI development in open-source ecosystems** demonstrates the continent's potential to lead in **language technologies and localisation efforts**.

SMART indicators

- Fund **500 AI projects addressing African development challenges by 2030**
- Establish **national AI innovation funds in at least 20 African countries**
- Support **cross-border AI collaboration programmes focused on public-sector innovation**

- Focusing AI innovation on African challenges will help ensure that AI development contributes to **inclusive economic growth and social impact**.

10.3 Final Policy Insight

Taken together, these policy recommendations highlight that strengthening Africa's AI ecosystem requires simultaneous investment in infrastructure, talent development pathways, open-source communities, and governance capacity. Addressing these areas will enable Africa not only to meet growing domestic demand for AI talent but also to position itself as a globally competitive hub for AI innovation and development.