

AI Made in Africa: Voices from AI businesses across Africa

Amplifying the perspectives of African AI businesses to drive meaningful growth

October 2026

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October 2026

Foreword

Across Africa, businesses are developing artificial intelligence solutions to address challenges in healthcare, agriculture, education, finance and other sectors. Their work demonstrates that Africa is not only adopting AI but is increasingly creating technologies shaped by the continent's needs and realities.

Yet these businesses face significant barriers to growth. High cloud and computing costs, shortages of specialised talent, limited access to appropriate financing, fragmented data ecosystems and evolving regulatory frameworks continue to constrain their development. Most notably, 65% of surveyed businesses identified limited customer trust and AI literacy as a scaling barrier, highlighting the importance of building public understanding and confidence alongside technological capabilities.

AI Made in Africa: Voices from AI Businesses across Africa brings these realities into the policy and investment debate. Based on the mapping of 311 AI businesses, a continent-wide survey and stakeholder interviews, the report provides evidence on what African AI businesses are building, how they operate and what they need to scale.

The findings highlight opportunities for coordinated action by governments, development partners and investors to improve access to affordable computing infrastructure, locally relevant data, specialised skills and patient capital. More responsive public procurement, harmonised rules for cross-border data flows and regulatory sandboxes could also help businesses innovate responsibly and expand across markets.

Through its longstanding cooperation with the African Union, Germany, through GIZ, has supported the development of the AU Data Policy Framework and the Conceptual Framework for the AU Continental Artificial Intelligence Strategy. Under the Data Governance in Africa Initiative, GIZ also supports data policies and strategies at national, regional and continental levels, helping to lay the foundations for a vibrant AI ecosystem that uses data safely and securely.

The AI Made in Africa initiative complements this cooperation by strengthening the evidence base for policymaking and ensuring that African businesses inform the policies, investments and partnerships intended to support them. I thank Briter, the participating businesses and all other contributors to this report. I hope its findings will inspire concrete action and stronger partnerships that enable African AI businesses to grow, compete and contribute to the continent's development.

Dr. Tobias Thiel

Director, GIZ African Union
Addis Ababa, Ethiopia



About us

The Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH is a global service provider dedicated to sustainable development and international cooperation. As a public-benefit federal enterprise, GIZ supports the German Government, primarily the Federal Ministry for Economic Cooperation and Development (BMZ), along with various public and private sector clients, in achieving their international objectives across approximately 120 countries. Since 2004, the African Union (AU), in partnership with the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ), has worked to advance inclusive growth and sustainable development in line with Agenda 2063. With a staff of approximately 250, GIZ African Union collaborates with the African Union Commission and specialised agencies such as AUDA-NEPAD across more than 40 AU member states, focusing on key areas such as governance, sustainable economic growth, and peacebuilding.

AI Made in Africa is a GIZ initiative implemented by the GIZ Office to the African Union, based in Addis Ababa, Ethiopia. With a focus on the private sector, AI Made in Africa advances evidence-based AI policymaking, generates data and insights on the African AI ecosystem through the AI Business Survey, and supports the development of AI ecosystem resources to strengthen innovation across the continent. The initiative also contributes to continental, regional, and national AI policy dialogues, supporting the implementation of the AU's vision for a responsible, inclusive, and competitive AI ecosystem in Africa.

AI Made in Africa commissioned the report, AI Made in Africa: Voices from AI businesses across Africa, to generate comprehensive evidence on the continent's AI business landscape. The initiative led the overall research design, survey methodology, and the development of the business ecosystem dataset and analytical framework. The findings are intended to inform policy processes in Africa, strengthen support for African AI businesses, and contribute to evidence-based investment, policymaking, and capacity-building across Africa's AI ecosystem.

Briter Bridges Ltd (Briter) is a data and market intelligence firm delivering insights into emerging markets across Africa, Latin America, and Asia. Briter collects innovation ecosystem data, including company, investor, ecosystem support and enablement organisations using its proprietary AI-enabled data collection methodology. Briter also leverages networks across emerging markets to enrich and validate the collected data. Briter Intelligence provides a platform access to company, investor, and funding data through interactive dashboards and customisable insights. Briter uses its proprietary data to conduct insightful research on innovation ecosystems, sectoral analysis, and deep-dives into digitally-enabled technologies across emerging markets. More information can be found on briter.co.

Briter is a research partner for this project, mapping AI businesses and the related ecosystem across Africa, designing and conducting the AI Business Survey, conducting stakeholder engagement, and writing the report.

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Executive summary

Ecosystem snapshot

311
African AI businesses mapped

85
African AI businesses analysed in the survey

35+
Sectors in which AI businesses operate

$1.3B
Funding mobilised by African AI businesses (2016-2025)

$225K
Median ticket size raised by African AI businesses (2016-2025)

This report presents findings from **311 AI businesses across Africa**, alongside 85 African AI businesses that responded to the 2026 African AI Business Survey between April and July 2026, supplemented by interviews with 16 AI businesses, ecosystem support organisations and regulators.

AI is becoming increasingly central to the operating models of surveyed AI businesses. Broader mapping of AI businesses showed that the majority were adopting AI technology into existing services, but a targeted survey showed that 75% of respondents consider AI-based products and services as core components of their operating models. This trend is concurrent with the expansion of GenAI tools since 2022, which have broadened access to advanced AI and machine learning capabilities. These developments highlight the importance of strengthening an enabling environment for inclusive, sustainable, and responsible AI innovation across Africa.

Key challenges

- **Customer trust and AI literacy need to be improved for consumer-level AI adoption.** Companies report spending significant time educating customers, demonstrating AI reliability, and overcoming scepticism around model performance. These challenges are further compounded by the limited contextual performance of many globally trained AI models in African settings. Long procurement processes, legacy systems, and data quality challenges also continue to slow adoption.
- **Lack of high quality data.** One third of surveyed AI businesses pointed out that the lack of data availability, which also leads to high development costs, is one of the leading barriers to scaling. Businesses often spend a long time consolidating available public data, such as land use or satellite data, and spend a lot of resources to fill the gaps.

How the ecosystem is reacting

- **Surveyed African AI businesses are not fixed on one consumer segment, but diversifying commercial pathways.** 88% of surveyed companies target other businesses and 44% target the government as customers. Surveyed AI businesses frequently serve multiple customer groups simultaneously to diversify revenue streams and build market resilience.
- **AI Businesses develop their own datasets.** The first wave of African AI businesses already acquired consumer or topical data through existing products and services, and they utilise AI as a technical layer to improve the product.

- **There is an asymmetry between the cost and the price of AI services.** Over half of surveyed AI businesses price their products under $2,500 annually per customer. Additionally, 65% of surveyed AI businesses cite cloud and compute costs as their single highest cost ahead of data acquisition. Given that Africa accounts for less than 1% of global data centre capacity despite hosting approximately 18% of the world's population, the vast majority of AI computation is happening on foreign servers, and access to them is denominated in foreign currencies. This creates a structural asymmetry where AI companies absorb costs of internationally benchmarked infrastructure (APIs, GPUs, globally priced cloud infrastructure) while selling into lower-income operating environments.

- **AI talent scarcity is a structural problem.** Africa holds just 1–3% of the global AI talent pool[2], and senior technical roles are acutely difficult to fill. More than half of surveyed companies say AI research roles are the hardest to hire for, followed by MLOps and infrastructure roles.

- **The data suggests that the cost of AI infrastructure shapes the AI tech stack of surveyed African AI businesses.** At the earliest stages, companies spread relatively evenly across in-house models, open source models, third-party APIs and hybrid combinations, which may reflect cost and accessibility as much as technical strategy. As companies raise more capital and move into the $1M–$10M funding band, hybrid architectures become increasingly accessible and therefore common. Companies layer proprietary datasets, fine-tuning systems, and workflows on top of open-source foundations to balance cost efficiency with competitive differentiation.

- **Surveyed AI businesses remain relatively lean, and they train in-house.** Most surveyed AI businesses operate with lean teams even when they have scaled: only 2% employ 250 or more people. Rather than waiting for external talent markets to improve, 47% of companies have responded by building formal internal training pipelines, hiring junior engineers and upskilling them into specialist roles.

What can help African AI business founders scale meaningfully?

- **More contextual funding in the space.** AI resources are helping companies and institutions run more efficiently. To drive further adoption and responsible development, AI businesses need high-quality data, deep expertise, and resources to test AI services to the real userbase. That data and infrastructure are expensive, which makes R&D cycles longer, and costs higher and harder to predict. While funding interest in AI businesses has been increasing, investors are focusing on AI businesses with commercial proof points, and many early-stage AI businesses are struggling to showcase that. This explains why 20% of businesses labelled increasing revenue, and 11% fundraising, as scaling priorities. On the investment side, founders are not simply asking for more capital: the qualitative data consistently surfaces a demand for patient, contextually literate investors who understand that B2G sales cycles in African markets typically run 12 to 18 months, that currency devaluation is a structural operating risk rather than an exceptional event, and that product-market fit in these contexts looks different from Silicon Valley benchmarks.

1. World Economic Forum (2025)
2. Businessday Tech & PwC Africa (2026)

- **Support for R&D and compute costs.** Surveyed AI businesses responded that R&D and compute subsidies (62%) and cross-border data harmonisation (49%) are two of the highest priority interventions. Businesses also increasingly seek specialised AI hubs that provide GPU access, localised datasets, regulatory expertise, and institutional partnerships rather than generic business support infrastructure. Many surveyed AI businesses across Africa want two things: lower input costs and a stronger business case.
- **Offset the talent training burden.** Senior AI research roles are the hardest to fill for surveyed AI businesses, so they are increasingly training junior staff in-house. In addition, surveyed AI businesses are competing with global companies for talent, and often cannot compete on pay. Founders suggested that targeted support and subsidies to offset the cost of training, ecosystem building, and upskilling are crucial for developing and retaining the talent pool within their local ecosystem.
- **Being able to clarify policy questions.** Regulatory uncertainty is one of the scaling barriers surveyed African AI businesses face, and one of the main reasons they would participate in a regulatory sandbox. 18% of surveyed businesses reported that they would participate in a regulatory sandbox in order to access to regulatory experts and further clarity on how they should comply with emerging policies on data localisation and data protection laws.

Introduction

Artificial intelligence (AI) is increasingly recognised as a vital catalyst for addressing Africa's social, economic, and environmental challenges and advancing the aspirations of Agenda 2063[3] through inclusive and sustainable development. Businesses across Africa are developing innovative AI solutions in healthcare, education, civic and legal services, agriculture, finance, and beyond. These emerging businesses are utilising existing AI capabilities to develop novel, context-appropriate ones. These new AI capabilities serve business and individual consumers across the continent who want AI that's more context-appropriate and localised.

While AI-enabled businesses across Africa are on the rise, they continue to face significant infrastructure and ecosystem challenges, including access to data centres, graphics processing unit (GPU) capacity, cloud infrastructure, high-quality datasets, and AI models that adequately reflect African contexts. A more grounded understanding of the realities of building, expanding, and commercialising AI services and products across Africa is needed to inform evidence-based policies, investment, and ecosystem support that can accelerate the adoption and development of these solutions.

To harness the potential of AI-enabled innovation, GIZ is implementing the "AI Made in Africa" project, which aims to strengthen the foundational requirements for AI utilisation in the continent's economic development in support of Africa's digital transformation objectives.

This report analyses the African AI business landscape using historical data and recent survey results. The report shows how the ecosystem has evolved over time, what issues and opportunities are currently affecting the ecosystem, and how different actors should shape the next stages of this fast-evolving ecosystem. The report also introduces case studies from AI businesses to amplify voices from the ground, showcasing a few areas on how the ecosystem can drive meaningful growth of AI across the continent. This report delivers the analysis in the following order:

- **Section 1**
  Identifying AI businesses across Africa
  presents the headline findings from a stakeholder mapping African AI businesses alongside the operational footprint of the surveyed AI businesses.
- **Section 2**
  AI tech stack and usage across companies
  unpacks how businesses source their AI capabilities and how that choice varies by sector and tech stack.
- **Section 3**
  AI business models
  connects company age to commercial outcomes, including customer segmentation and pricing.
- **Section 4**
  Funding AI businesses in Africa
  explores the fundraising landscape for African AI Businesses through funding instruments, funders, and location.
- **Section 5**
  Ecosystem bottlenecks and infrastructure challenge
  identifies the binding constraints on scaling, such as customer trust and literacy, AI talent scarcity, and cloud/compute infrastructure dependency.
- **Section 6**
  Ecosystem needs for public-sector intervention
  shows the surveyed results on the most needed policy interventions and partnership models for the African AI businesses.

3. A 50-year plan set out by the African Union to guide the continent's social and economic growth from 2013 to 2063. See more about the initiative here.

Methodology

The data collected in this study aims to generate evidence-based insights into the African AI business landscape, focusing on business characteristics, growth patterns, constraints, and opportunities across all African Union (AU) regions, sectors, and language groups. To achieve this, the research employs a mixed-methods design, combining comprehensive stakeholder mapping, a continent-wide AI business survey, and targeted qualitative interviews to capture both the scale and depth of the ecosystem.

The quantitative foundation of this research draws on the Briter Intelligence database, which tracks a universe of 4,000+ technology companies with 7000+ disclosed funding information between 2016 and 2025. The disclosed funding amount in this report is denominated in USD ($). Using Briter Intelligence data, the research team identified 311 AI businesses that (1) show active development or adoption of AI technology (AI-centric), (2) have for-profit business models rather than non-profit models, and (3) have operational presence in Africa. These entities were validated and screened for AI centrality, distinguishing between "AI-native" businesses and "AI-enabled" businesses (defined below). Further, the African AI businesses were classified by operational age, sector, and size. This pool formed the basis for the African AI Business Survey 2026, which collected structured data across all five AU-recognised regions to provide comparable metrics on AI adoption, talent, and market constraints.

The African AI Business Survey 2026 was co-developed by GIZ through the "AI Made in Africa" project in collaboration with Briter. The survey consists of 60 total questions, with 7 key question groups: (1) company information, (2) AI technology adoption, (3) talent and skills, (4) data and infrastructure, (5) policy and regulation, (6) partnerships and ecosystem, and (7) funding snapshot. The survey was hosted on GIZ's Kobo platform and was accessible via an online link. The survey is available in English, French, Arabic, and Portuguese. The survey was sent directly to AI businesses identified in the mapping phase via emails, social media, and WhatsApp, and indirectly through social media posts and through the communication channels of various ecosystem support organisations. The report uses survey responses collected between April and July 2026, and out of 102 responses, 85 responses from unique AI businesses operating in Africa were used for analysis. Responses that are not used in the analysis are: duplicate responses, incomplete responses, responses from businesses that did not adopt or develop AI, and responses from AI businesses that did not operate in Africa (some may have had African founders but operate in other regions or aspirations to operate in Africa but if they currently did not have operations in Africa).

Additional qualitative data were collected through semi-structured interviews and a closed-door validation session with 16 AI businesses and organisations. The semi-structured interviews were designed to contextualise the survey findings, exploring operational realities such as business model development, the reasons behind the challenges AI businesses experience in accessing infrastructure and compute resources, and how they navigate emerging regulatory environments. In addition to one-on-one discussions, we also held a small closed-door consultation with a select group of ecosystem actors from across the African continent. This provided an opportunity to gather additional perspectives on the emerging findings, rather than serving as a comprehensive validation exercise. The list of interviewees and participants in the validation session can be found in the annex.

Data privacy

Data privacy and ethical compliance: Our research methodology adheres strictly to GIZ's data protection standards and global ethical research frameworks, ensuring that all ecosystem intelligence is gathered with respect for participant confidentiality. We prioritise the principle of data minimisation, collecting only the essential information required to fulfil the research objectives. All participant engagements are conducted on a voluntary basis and with an informed consent process. The raw data collected during this process is stored per GIZ's and Briter's respective data protection regulations. GIZ's data privacy consent form was also shared with survey participants.

Data handling and security: To safeguard participant confidentiality, we anonymised survey responses in the analysis, and only mention identifiable individual answers with the consent of the select companies we interviewed after the survey (list in the annex). All project data is stored in secure, encrypted environments, with access restricted exclusively to the core research team. This commitment to data integrity and security ensures that our findings are both evidence-based and aligned with the highest standards of privacy, reflecting our dedication to ethical research practices within the African innovation ecosystem.

For more information about data privacy and forms used in the study, please visit giz.de/en/data-protection.

Limitations of the study

The quantitative analysis draws on a non-exhaustive sample of AI businesses operating across Africa. Consequently, the dataset may underrepresent very early-stage ventures, stealth startups, and companies with limited online presence. Geographic coverage is also uneven, with Northern and Central Africa underrepresented relative to other regions. In addition, the survey sample differs from the broader mapped dataset, including a higher representation of AI-native companies. These differences in sample composition should be considered when interpreting findings that represent the entire African AI ecosystem.

Funding data is biased towards publicly disclosed capital, meaning frequently undisclosed sources of funding remain outside the scope of this research. Survey responses also varied across individual questions, as not all respondents answered every question. As a result, the number of observations underlying specific survey findings may differ, and findings based on smaller response counts should be interpreted accordingly.

While the survey was conducted in multiple languages to ensure broad accessibility, its primary distribution via online channels may have limited visibility among specific communities. As this report represents the first research iteration of its kind, the methodology establishes a baseline that will benefit from further refinement, longitudinal data collection, and expanded outreach in future assessments.

Key terms

AI business
For this study, AI businesses are defined as for-profit businesses that develop AI-native products or integrate AI as a significant component of products and services offered in African markets. Businesses that are not yet profitable, but operate with a for-profit model and for-profit businesses that have a non-profit arm are both considered as AI businesses in this research.

AI-enabled
AI enhances an existing product or process, but the company could operate without it, at reduced effectiveness. (Example is an ID verification tech company which integrates AI analytics to identify pictures or catch fraud.)

AI-native
AI is fundamental to the product and the company's value proposition, and revenues depend directly on AI-based capabilities. Remove the AI and the product ceases to exist. (Example is an autonomous solar-powered robot company that uses AI to automate its movements and activity scope.)

API (Application Programming Interface)
A mechanism that allows one piece of software to access the functionality of another. In this report, third-party API refers specifically to commercial AI capabilities accessed via external providers (such as OpenAI, Anthropic, or Google), where companies pay recurring, usage-based fees rather than building or hosting models themselves.

CPU (Central Processing Unit)
The general-purpose processor used to run standard computing tasks. Unlike GPUs, CPUs are not optimised for the parallel processing required to train or run most AI models efficiently, and are typically referenced in this report in contrast to GPU-dependent infrastructure costs.

Entity size
The size of employees working for the business at the time of reporting. In the research, the entity size brackets are grouped as: Micro (1-10 employees); Small (11-50); Medium (51-250); Large (251+).

GenAI (Generative AI)
A class of AI models capable of producing new content based on patterns learned from training data, rather than simply classifying or analysing existing information. In this report, references to the GenAI boom refer to the rapid public availability of foundation models like GPT, Llama, or Mistral from 2022 onwards, which lowered the technical and capital barriers to building AI-native products.

GPU (Graphics Processing Unit)
Specialised hardware optimised for the parallel computation required to train and run AI models. GPU access is a major cost driver for AI businesses, particularly those building or fine-tuning in-house models, and is typically priced and denominated in USD regardless of a company's operating market.

MLOps (Machine Learning Operations)
The set of practices, tools, and infrastructure used to deploy, monitor, and maintain machine learning models in production. Referenced in this report in relation to hybrid AI businesses and the infrastructure support needed to help companies transition from single-source AI architectures (pure open-source or pure API) to more complex hybrid setups.

Operational only in Africa
An AI business whose operations exist only in Africa. This can be an AI business that operates in one country or more, but all of its operations occur on the African continent. Operational countries can be separate from the headquarters location, where a business

operational only in Africa can be headquartered in an African country and/or set up an administrative or financial headquarter outside of Africa while maintaining the operations and the consumer base within Africa.

Operational beyond Africa

Compared to AI businesses operational only in Africa, an AI business operational beyond Africa is one that operates outside Africa as well as within Africa. Businesses operational beyond African can be headquartered both within Africa or outside of Africa.

Regions

African Union (AU) regional groupings: Northern, Western, Eastern, Central, and Southern Africa. Sub-regional distinctions (Anglophone vs. Francophone West Africa; established hubs vs. frontier markets) are introduced where the data supports them and not applied where it doesn't.

Responses

For survey questions that allowed to select more than one answer, percentages in this report represent the proportion of respondents who selected each option. Analysis drawing from multiple-selection questions are indicated in the footnotes. Because respondents could select more than one option, percentages may sum to more than 100%.

Section 1: Identifying AI businesses across Africa

Key points

- AI businesses are spread across Africa, with expected concentration in hubs like Kenya, South Africa, Egypt, and Nigeria.
- Most surveyed AI businesses operate within Africa, while approximately one-fifth also have operations outside the continent.
- African businesses are often cross-border, as one-fifth of the surveyed AI businesses operate in more than five countries.
- AI solutions in Africa are not all applied solutions. There are a lot of AI-as-a-Service software companies that are helping users adopt AI further in their business or operations.
- AI is also applied across key sectors such as Agriculture, Health, and Finance, although the access to high-quality data appears to affect their scalability.

African AI is developing across a diverse and rapidly evolving ecosystem, but the businesses building it are not evenly distributed across markets, sectors, or stages of maturity. This section maps the shape of that ecosystem: where AI businesses are concentrated, when they were founded, what sectors they serve, and how large or mature they are. Together, these patterns provide a baseline for understanding who is building AI in Africa before looking more closely at how they build, sell, and scale. The following section explores the combined analysis of the broader mapping and survey responses.

Overview

The study identified over 300 businesses that are developing AI products and services or integrate AI technologies as a core part of their products and services. AI businesses in Africa are visible across incubation and acceleration programmes and publicly disclosed fundraising records. The survey responses represent just under a third of the mapped ecosystem, and is used as a sample to enrich the mapping's regional and structural patterns with direct company reporting. This surveyed sample is comparable with the mapped dataset in many ways, but with some notable additions: survey respondents reported on their business model, tech and AI usage, operational age, and policy interactions in far greater depth than the mapping alone could capture. That additional depth is what enables the bottom-up analysis in the sections that follow. Moving from where AI businesses are and what they do, which the mapping already establishes, to how they actually operate: their commercial models, technical choices, revenue and fundraising stage, and the ecosystem-wide challenges they report facing directly. The sections ahead draw on both datasets together, using the mapping to anchor the broader population and the survey to explain the behaviour within it.



Figure 1: Map of AI businesses by African Union regions[4]

Source: Briter Intelligence (2026)

4. Note: Figure 1 showcases a sample of AI businesses that responded to the African AI Business Survey 2026, as well as companies mapped through Briter Intelligence. The companies are organised by 5 African Union regions, and ordered alphabetically. For this study, AI businesses are defined as for-profit businesses that develop AI-native products or integrate AI as a significant component of products and services offered in African markets.

Geographic distribution

Most of the surveyed businesses operate only within Africa, but about one out of five businesses operate beyond Africa. Operational countries of the surveyed AI businesses span across 38 African countries and 21 countries outside Africa. The top operational countries of African AI businesses that responded to the survey are Nigeria, Kenya, Ghana, South Africa, United States, Côte d'Ivoire, and Tanzania.

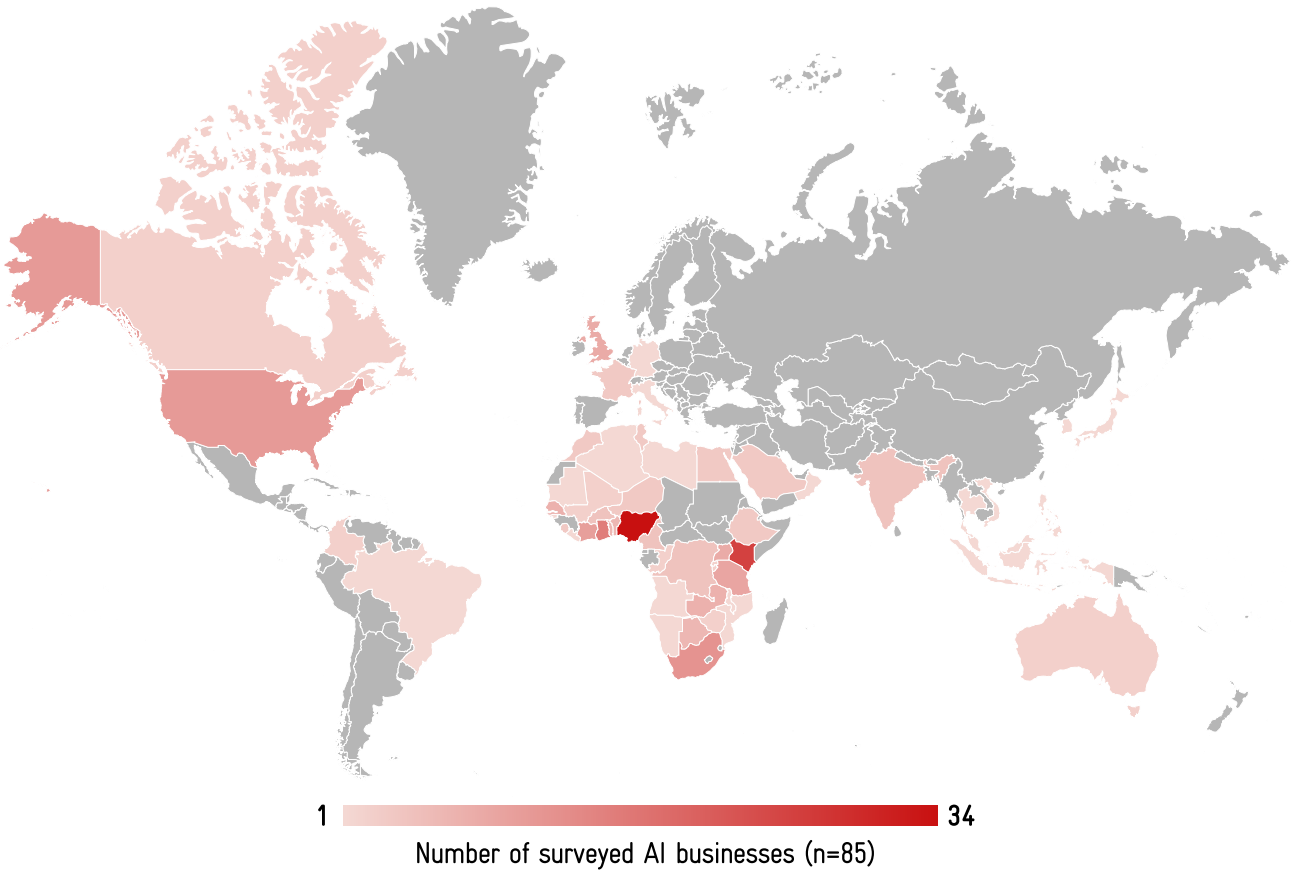


Figure 2: Operational countries of surveyed AI businesses Source: African AI Business Survey (2026)

Placed side by side, the mapped and surveyed datasets tell a consistent regional story: activity is concentrated in Western and Eastern African with Kenya, Nigeria, Ghana and South Africa serving as hubs. The Central African ecosystem still seems nascent both from the mapping and the survey. While the mapping showed a sizeable growth of the Northern African region, the survey did not capture as many Northern African AI businesses[5]. Another notable difference is that 19% of the surveyed companies were AI businesses with a global footprint, including active operations in Africa and other continents, while the mapped companies were mostly regional. The survey provides more insights into cross-border behaviour, which the mapping alone can't capture. While 57% of surveyed AI businesses operate in just a single country, the remaining 43% show real geographic mobility: 20% operate in over five countries, and 6% operate across 10+.

5. The survey was made available in both Arabic and French, in addition to English and Portuguese, to help bring in more Northern African respondents.

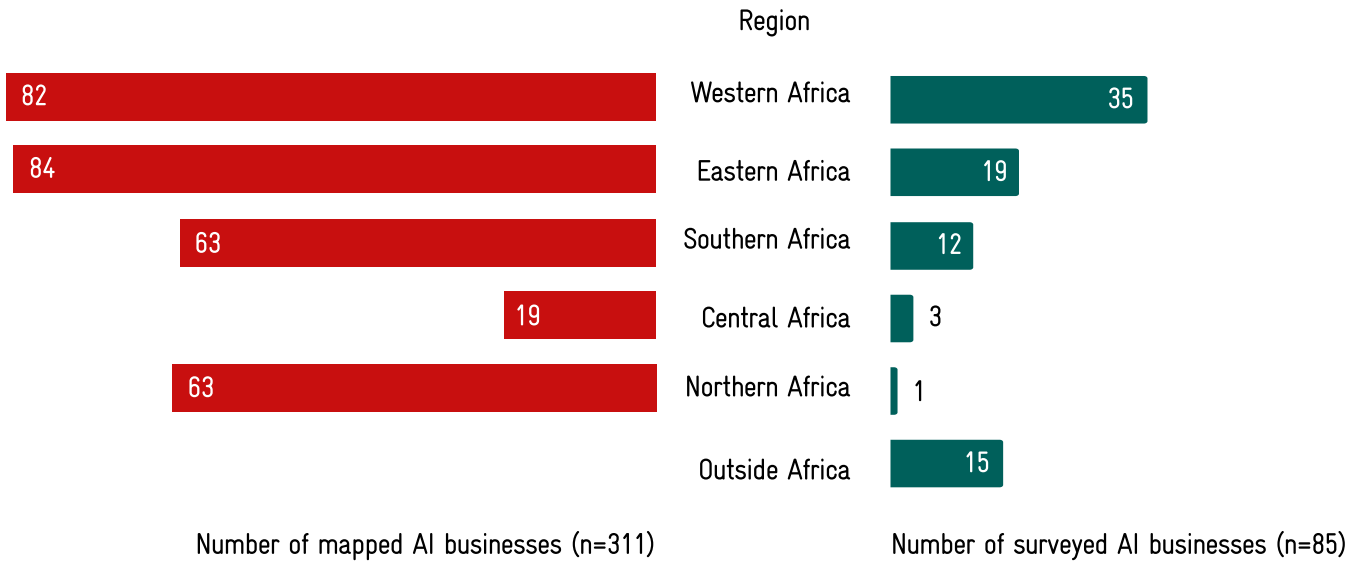


Figure 3: Number of mapped versus surveyed AI businesses by African region

Source: Briter Intelligence (2026), African AI Business Survey (2026)

The range of operational footprints among surveyed companies is wide. At the smaller end, some prioritise a few markets, like Danaya's KYC and compliance technology, which spans Côte d'Ivoire and Senegal, two Francophone Western African markets sharing regulatory heritage and language. In Eastern Africa, Acre Insights' farm monitoring and drone-based management operates across Kenya and Rwanda, neighbouring Eastern African markets with comparable smallholder farming contexts.

At the other end, Ignitia shows what pan-African scale looks like. Ignitia, a global AI weather forecasting company with some operations in Ghana, has taken its satellite-dependent model across 18 African countries and into Brazil, Colombia, and Indonesia, which is a structural advantage of not depending on ground infrastructure in each new market.

Sector distribution

Both mapped and surveyed AI businesses operate across a few key sectors, including software, agriculture & agtech, health, education, fintech, and logistics & mobility. Software is the largest sector by number of companies, but beyond that, the two datasets diverge in interesting ways. Agriculture & agtech is the second-largest sector in the mapping, nearly rivalling software in size, but it shrinks substantially in the surveyed dataset, landing behind both health and education. This gap suggests one of two things: either agriculture AI businesses are harder to reach through a direct survey and less inclined to respond, or the mapping's screening methodology overstates the sector's actual scale compared to what self-reported data shows.

AI businesses providing services in the health sector shows up frequently in both mapped and surveyed businesses. Health ventures often have to work with complicated regulatory environments but once they are embedded into a system, they are able to deepen their data coverage and develop more relevant AI solutions. The education sector showed up larger in the mapping exercise but smaller in the survey. Education tech companies, similar to the health sector, often work with institutions or governments which may have a higher barrier to entry and low access to reliable data, but once in the system, they are able to scale through institutional partners. Fintech and logistics & mobility are the smallest categories in both datasets, not because these industries are not adopting AI, but likely because the some of these more mature tech industries are likely adopting AI businesses through existing partnered companies that are integrating AI to improve their operations rather than through new AI businesses.

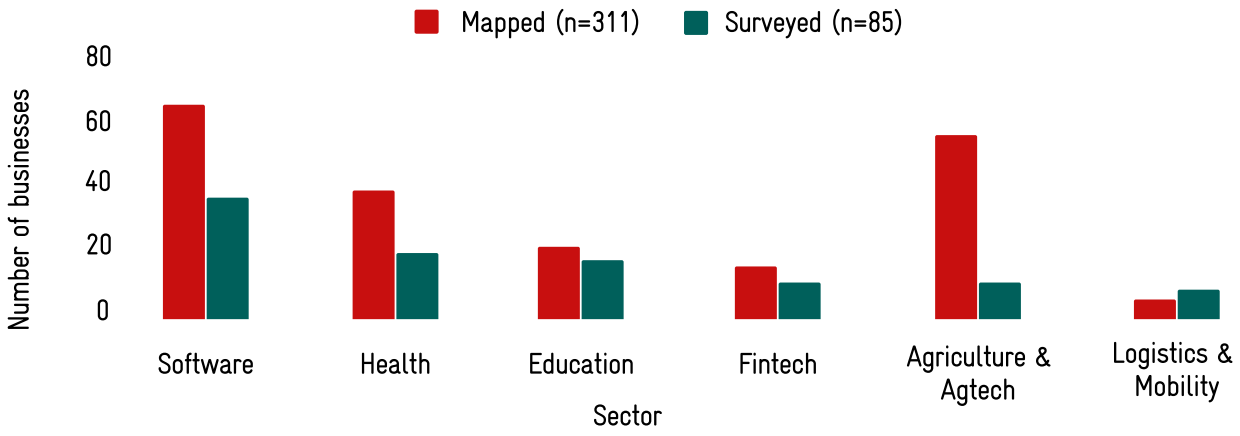


Figure 4: Number of mapped versus surveyed AI businesses by top sectors

Source: Briter Intelligence (2026), African AI Business Survey (2026)

Box 1: AI products across sectors: what African AI is actually being built to do

In health, an example of AI is diagnostic and clinical decision support. African health systems are severely under-resourced in specialist diagnostic capacity, making AI a potential force-multiplier for frontline workers. However, the concentration of products in diagnostics also carries risk. Diagnostic AI trained on non-local datasets produces unreliable outputs in African clinical contexts, meaning that the value of these products is directly contingent on local data availability and model fine-tuning. **The implication is that health is a sector exposed to reliability failures if data infrastructure constraints are not addressed alongside product development, data protection challenges, and ethical concerns of how that data is used.**

In agriculture, AI products often are tackling either field-level intelligence or supply chain infrastructure. This dual focus reflects the two-sided nature of the agricultural productivity gap on the continent: farmers lack both the agronomic information to optimise their practices and the financial identity to access credit and markets. What makes agriculture distinct is how thin the underlying data is on both sides: smallholder farms generate far less digitised data than, say, mobile money users or hospital patients, which makes solving either half harder, and solving both together more valuable.[6] **A product that solves only field-level intelligence or only financial access is solving half a problem in a sector where the underlying data challenges are already unusually acute.**

In fintech and regulatory tech, the focus is on automation of high-friction processes. This is a natural fit for AI because these processes are rule-bound, data-intensive, and currently expensive to execute manually. Fintech AI in Africa is primarily a cost-reduction and access-

6. phys.org (2026)

expansion play rather than a product innovation play. **This matters for how investors evaluate these companies: the value proposition is cost and efficiency, reducing the labour and time required to run processes the business already does, rather than introducing a new consumer-facing capability.**

In logistics and energy, AI is applied to operational optimisation. These applications need to function reliably in low-connectivity environments due to physical hardware present in these products, which shapes both the technical architecture and the commercial model (enterprise contracts with large operators rather than consumer-facing products). **That hardware dependency is what insulates the sector from the trust and adoption problems facing consumer-facing sectors like health or agriculture: because the product is embedded in equipment operated by sophisticated institutional buyers evaluating operational metrics, there's no equivalent of an individual consumer needing to be persuaded to trust an unfamiliar AI tool.**

The African AI ecosystem is young, concentrated, and increasingly AI-native, with a growing cohort of businesses building around AI rather than simply adding it to existing products. But the headline growth in company formation masks significant differences in where businesses are located, which sectors they serve, and how far they have progressed toward scale. The next section moves from who is building AI to how they are building it, examining the technical architectures, data sources, and development choices shaping surveyed African AI businesses.

Section 2: AI tech stack & usage across companies

Key points

- AI sourcing strategies appear closely linked to capital access and data constraints; interviews indicate these weigh heavily alongside technical preference.
- AI centrality reveals meaningfully different commercial and technical dynamics. AI-native companies face longer sales cycles and higher customer acquisition costs; AI-enabled companies benefit from an existing customer relationship but must prove the AI adds real value.
- The survey's AI-native share (75%) is notably higher than the full mapped dataset (44%). AI centrality by founding year shows newer cohorts are AI-native at much higher rates than older ones. It also shows a broader shift from AI-adoption to AI-creation that the newer companies captured in the survey reflects.
- Sourcing strategies shift with company age. Early-stage companies split evenly across in-house, open source, API, and hybrid approaches; hybrid becomes dominant at growth stage and beyond, as companies layer proprietary capabilities onto open foundations once they can afford to.

Surveyed African AI businesses are not building from a single technical blueprint. Their approaches vary depending on when they were founded, the markets they serve, and the resources available to them. This section looks at how the ecosystem has evolved across founding cohorts, what companies are building, and where the technology powering these businesses comes from, from proprietary models to open source tools and third-party APIs.

AI centrality

Understanding how central artificial intelligence is to a company's core product and revenue model, or AI centrality, is a useful lens for analysing how AI adoption is actually happening at the business level across Africa. Rather than treating AI businesses as a single category, distinguishing between companies for which AI is the product and companies for which AI improves an existing product reveals meaningfully different commercial dynamics, scaling challenges, and policy implications.

This report uses two levels of AI centrality to assess how essential AI is to a business's core value proposition and revenue model: An **AI-native** company is one where artificial intelligence is fundamental to the product itself. The company's value proposition and revenue depend directly on AI-based capabilities, and removing AI would mean the product ceases to exist. An **AI-enabled** company, by contrast, uses AI to enhance or optimise an existing product or service, but could continue to operate without it, albeit at reduced effectiveness.

Out of the 311 AI companies mapped through the Briter Intelligence database, 44% are AI-native and the remainder are AI-enabled. Of the surveyed businesses, 75% are AI-native and 25% are AI-enabled. This divergence is likely explained by two factors. First, there is a degree of selection bias: AI-native founders are more likely to seek out and complete studies like this one, viewing participation as a way to access shared learnings and contribute to a conversation that is directly relevant to their business model. Second, the survey over-represents the post-2022 founding cohort, since founders who built AI-first from day one tend to be more recently established, more publicly visible, and more engaged with the broader African AI ecosystem conversation.

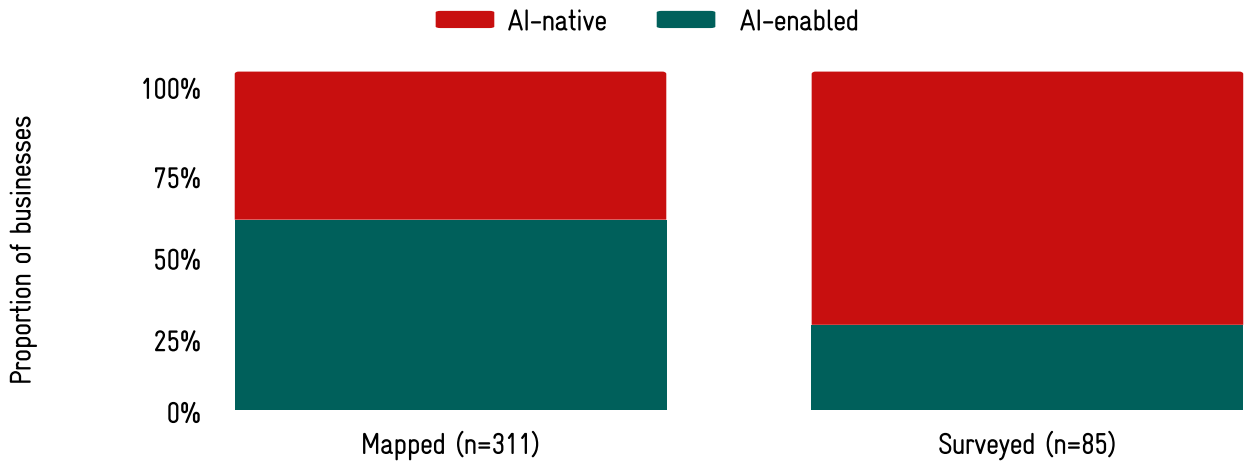


Figure 5: Proportion of mapped versus surveyed AI businesses by AI-centrality Source: Briter Intelligence (2026), African AI Business Survey (2026)

Looking across sectors, **AI-native** companies are most prevalent in software, which functions less as a sector in its own right and more as a catch-all for companies building AI capabilities, tools, and platforms that can be applied across industries. These are companies creating the foundational AI services on which other businesses can build, rather than targeting a specific end-use case. Alongside this horizontal software layer, pockets of AI-native companies are emerging in specific industry verticals: health, agriculture & agtech, fintech, logistics, and education are all producing AI-native businesses that have built AI into the core of what they do from day one, rather than layering it on top of an existing service.

The commercial and operational implications of being AI-native are significant. Because the product is novel by definition, AI-native companies must educate the market on both the problem they are solving and the AI-driven solution simultaneously. This typically produces longer sales cycles, higher customer acquisition costs, and a greater need for trust-building. The Awareness Company, which builds AI-native products for enterprise clients, illustrates this clearly: they track detailed adoption and activation metrics to demonstrate value to customers, build revenue through longer-term enterprise contracts rather than quick transactional sales, and invest heavily in producing case studies and participating in ecosystem events to create visibility for products that buyers have no prior reference point for.

Beyond commercialisation, AI-native businesses also face distinct technical challenges. Developing proprietary AI models often requires specialised expertise, access to large volumes of domain-specific data, and significant investments in computing infrastructure. The experience of Acre Insights demonstrates how these technical capabilities become central to delivering AI-powered products in sectors where conventional analytical methods are insufficient.

Company Spotlight



Acre Insights

Building AI-native geospatial intelligence for farmers

HQ country



Kenya

Years of Operation	Sector	Operational Countries	AI Centrality
3	Agriculture & Agtech	Kenya, Rwanda	AI-native

Acre Insights is a Kenyan geospatial intelligence company founded to measure and monitor large-scale nature-based projects using drones and satellite imagery. The company initially focused on estimating avocado yields and later pivoted after finding that traditional approaches produced error margins that were too high for commercial use. Acre Insights developed AI-powered models that analyse satellite imagery, drone data, and environmental variables to estimate biomass, monitor ecosystem restoration, and support carbon offset projects. Rather than relying on AI as an add-on, the company's products depend on machine learning to identify complex relationships between terrain, weather patterns, and vegetation that cannot be modelled using conventional statistical methods.

Building these AI-native products requires overcoming several technical and operational challenges. The company works with vast amounts of unstructured spatial data that create significant cloud storage costs, while remote field operations often require data to be stored locally because internet connectivity is unreliable. Acre Insights hires graduates with backgrounds in Geographic Information System (GIS), computer science, and data modelling but then develops their AI capabilities through intensive in-house training. The company also works closely with aviation authorities to navigate drone regulations that affect the deployment of geospatial technologies across Eastern Africa.

> AI is an incredibly important tool for us because it can easily turn raw data into insights. Different slopes and weather patterns do not have a linear correlation, so we had to build AI models to understand those relationships.
>
> — **Catherine Njeri, Founder**

AI-enabled companies tend to be concentrated in existing industry verticals rather than in the software or infrastructure layer. Their defining characteristic is that AI improves a product or service that already has a market, an established customer relationship, and an existing revenue model. Venille, which sells environmentally-friendly sanitary products, developed an AI-enabled menstrual tracking and education tool to fill knowledge gaps identified through its existing customer base.

The commercial dynamic for AI-enabled companies is meaningfully different from their AI-native counterparts. Because buyers are evaluating a familiar service first, with AI as a feature rather than the proposition itself, the primary trust

challenge is not establishing whether the product category is valid but demonstrating that the AI enhancement genuinely adds value over the non-AI version. Venille, for example, focuses on onboarding existing customers to a digital platform and building confidence that its AI health product is a meaningful addition to their relationship with the brand, rather than having to establish the menstrual health use case from scratch. The sales cycle is typically shorter, but the risk of the AI being perceived as unnecessary complexity or an unwanted addition to a familiar product is also real.

The surveyed dataset captures a broad subsection of the mapped AI ecosystem. While companies in the survey operate across all major sectors, there is a strong leaning towards AI-native companies, particularly in sectors like "agriculture & agtech" or "fintech", which are actually dominated more by AI-enabled technologies.

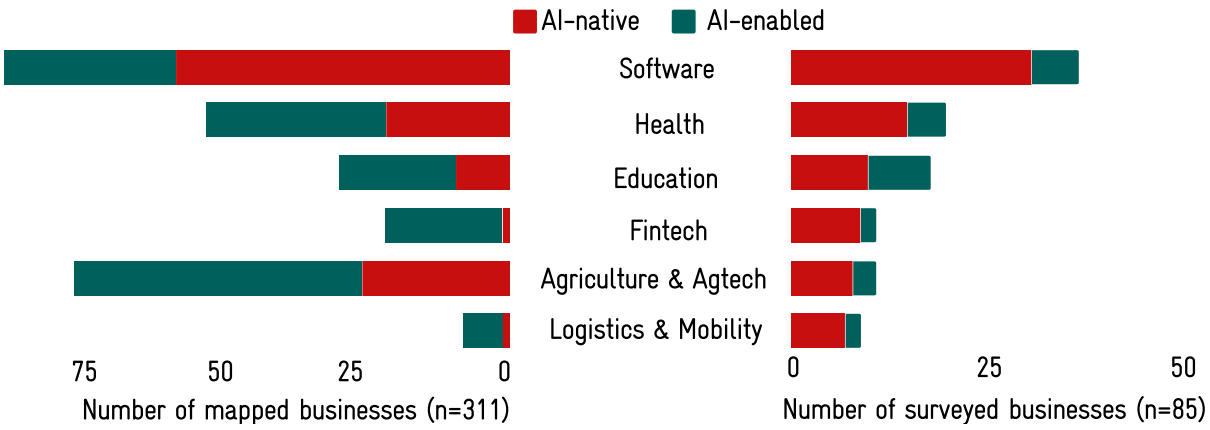


Figure 6: Number of mapped versus surveyed AI businesses by AI centrality and top sectors

Source: Briter Intelligence (2026), African AI Business Survey (2026)

AI source

A key question in this survey is how companies source their AI models. The data reveals four distinct approaches:

1. **In-house**
   Companies that build and train their own models from scratch

2. **Open source**
   Companies that use publicly available models (like Llama, Mistral, Stable Diffusion)

3. **Third-party APIs**
   Companies that access AI capabilities through commercial APIs (like OpenAI, Anthropic, Google)

4. **Hybrid**
   Companies that combine in-house models, open source models, and third-party APIs

It is worth unpacking what each of these sourcing strategies means in the African context specifically. In-house model development, which is building and training proprietary models from scratch, offers the greatest control over data privacy, model behaviour, and competitive differentiation, but it is also the most capital-intensive path. It requires large engineering teams, significant compute access, and long development cycles, all of which are structurally harder to sustain in an environment of high cloud costs and scarce senior AI talent.

Open source models such as Llama and Mistral offer a different trade-off: they eliminate recurring licence fees and per-query costs, converting a variable cost that scales with usage into a fixed infrastructure

investment. For companies operating under acute currency and cloud cost pressures, this matters enormously. Open source is not simply a cheaper option but often the only viable entry point for building capable AI products at all.[7] Companies like Soil Solutions, a Ghanaian soil health prediction and extension knowledge provider, choose an open source model as they are socially-oriented companies that want to democratise their AI-building process and integrate voluntary data from farmers. On the other hand, Venille, a Nigerian environmentally-friendly sanitary pad company that developed an AI chatbot to promote better menstrual health knowledge, opted to use existing open source large language models to be more resource efficient. They focused instead on building domain knowledge around their consumers' menstrual health practices. Third-party APIs sit at the opposite end of the control spectrum: fast to integrate, requiring minimal infrastructure investment, but introducing ongoing per-query costs, data sovereignty concerns, and dependency on external providers whose pricing and availability African companies cannot control. A company in our survey pointed out that they use third-party models due to their efficiency, trustworthiness, and for being a better fit for working with localised data.

The hybrid approach, which combines elements of all three, is most prevalent among GenAI and large language model (LLM) companies, consistent with a pattern where founders use open source foundation models as a cost-effective base and build proprietary layers on top, while selectively calling third-party APIs for capability where quality demands it. The global and practical consensus among builders is an increasingly hybrid one: run smaller open source models locally for cost and data privacy, and use proprietary API access for frontier capabilities.[8] African AI companies appear to be arriving at a similar conclusion, possibly sooner because of economic constraints.[9] This pattern is worth watching as these companies scale. A hybrid architecture built under cost pressure tends to produce leaner, more portable products than those built on top of a single proprietary provider and may prove to be a structural advantage rather than a compromise as model costs continue to fall globally.

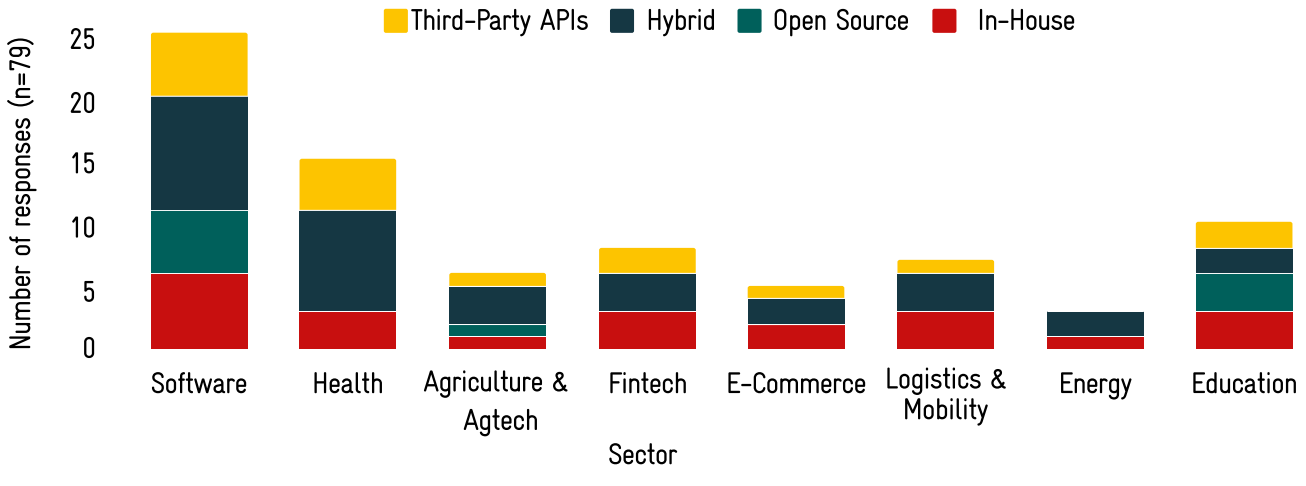


Figure 7: Number of surveyed responses by top sectors and AI source[10] Source: African AI Business Survey (2026)

7. HunterBI (2026)
8. arXiv (2026)
9. Kshetri (2026)
10. Note that the number of responses to this question is lower than the total number of respondents in the dataset, as not all respondents provided information on their AI source. This may reflect the proprietary nature of this information or, for earlier-stage businesses, the fact that a defined AI source has not yet been established.

Looking at the overall distribution of this surveyed dataset, approximately one-third of companies use in-house models, one-third use open source, and the remaining third are split between third-party APIs and hybrid approaches. However, this high-level view masks significant variation across sectors, tech stacks, and company operational age. A more detailed usage of compute methods across sectors is summarised in Box 2.

Box 2. What AI sourcing strategies reveal about constraints, not just choices

The dominance of in-house and hybrid models in health and agriculture may reflect data necessity as much as technical sophistication. General-purpose open source and third-party models are trained on non-African datasets that perform poorly in African clinical and agricultural contexts, producing unreliable diagnostic outputs, misidentifying crop diseases, or generating credit scores that do not reflect local repayment behaviour. Companies in these sectors are not building proprietary models because they have the resources to do so; they are doing it because off-the-shelf alternatives do not work well enough to be viable. **Investing in local-context training datasets for health and agriculture would not just benefit individual companies but can unlock the viability of a much wider range of AI applications in these sectors. By making open-source and API-based approaches more reliable, it reduces the capital intensity of entry for new players.**

The prevalence of third-party APIs in fintech reflects a dependency risk. Financial AI use cases are well-served by general-purpose models because the underlying tasks (language processing, pattern recognition, classification) are not context-specific. **But as fintech AI companies grow, the unit economics of API dependency turn unfavourable: per-query costs that scale directly with transaction volume, data sovereignty exposure when sensitive financial data is routed through foreign servers, and pricing risk from providers whose terms African companies cannot influence.**

Education's reliance on open-source and third-party API models is consistent with sector funding constraints; one possible explanation is that education AI companies, the most capital-constrained in the dataset, rely on models that avoid per-query costs. The practical ceiling this creates is real: open-source models without significant fine-tuning produce lower-quality outputs in local language contexts and low-connectivity environments, which limits the quality of learning experiences these products can deliver. **Closing the funding gap in education AI is therefore not just a commercial issue but a product quality issue, but the current funding environment makes that investment inaccessible for most.**

The logistics and energy sectors' skew toward in-house models points to a constraint that is infrastructural rather than financial: these applications need to run directly on local devices, without persistent cloud connectivity. This is not a cost optimisation decision but a functional

requirement, as a fleet management system that depends on a stable internet connection to a foreign cloud server is not viable in many African operating environments. **The implication for infrastructure investment is that edge AI capability is at least as important for these sectors as cloud access, and policy frameworks focused exclusively on cloud cost reduction will not address the constraint these companies actually face.**

Finally, the hybrid approach's prevalence among more mature and better-funded companies across all sectors reflects a convergence point rather than a starting point. Companies do not typically begin with hybrid architectures; they arrive at them after exhausting simpler approaches, accumulating proprietary data, and reaching the funding threshold where infrastructure investment is economically rational.

The practical implication for ecosystem builders is that supporting the transition from pure open-source or pure API approaches to hybrid architectures requires shared MLOps infrastructure, technical assistance programmes, or funding instruments specifically designed for infrastructure investment.

Taken together, the data suggest that capital and data availability play a major role in how the surveyed AI businesses build. Sourcing choices that look like technical strategy may partly reflect sector-specific data quality and funding constraints, although the survey cannot separate these from founders' own preferences. But, the ecosystem's shift toward AI-native companies is real and traceable across founding cohorts, not just a feature of who chose to respond to this survey. The next section looks at how these technical choices translate into commercial models, including who surveyed AI businesses are selling to, how they price their products, and how their business models evolve as they grow.

Section 3: AI business models

Key points

- Hybrid architectures become dominant at the growth stage; companies build on top of open source rather than abandoning it.
- Teams stay lean even at older operational ages. Most companies remain at 11–50 employees regardless of stage, with only 2% scaling past 250; a function of both AI-first efficiency and a still-young, talent-constrained ecosystem.
- The consumers of AI businesses are mostly institutional (88% B2B, 44% B2G); businesses only serving B2C segments are rare.

Building the technology is only one part of the equation. African AI businesses must also find customers, develop viable revenue models, and price products for markets where purchasing power is often constrained. This section examines who these companies serve, how they generate revenue, how pricing varies across markets, and how their commercial and technical models evolve as they scale.

Operating age of AI businesses

African AI businesses are not new, but they are still young. Across the full mapped dataset, most AI businesses sit in the growth stage (3-7 years old), 28% are early-stage (0-2 years), and only 23% are over 7 years old. The surveyed businesses land squarely inside that same window: the median age of surveyed African AI businesses is 5-9 years old, with a surge of new company formation in 2024.

The operating age story and the AI-native story follow the same trend, but from two angles. Pre-2021, new company formation was a mix of AI-native and AI-enabled entrants; from 2022 onwards, the recent cohort is almost entirely AI-native. The mapped dataset shows this shift across the full population of 311 companies, while the survey shows it again within its own sample of founding years. The two datasets converge around the same inflection point, which coincides with the public release of large foundation models and the rapid expansion of generative AI tools.

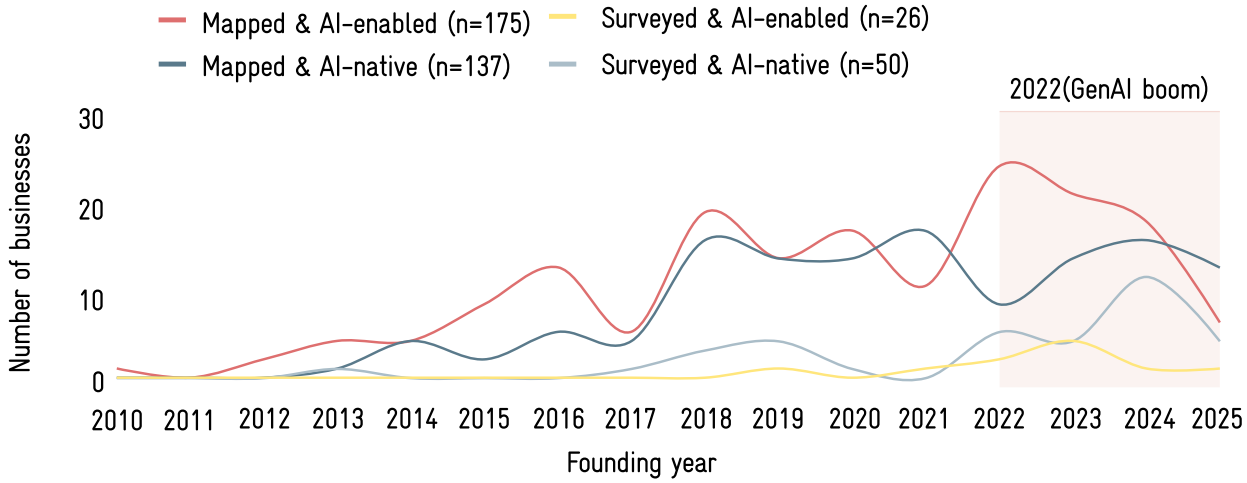


Figure 8: Number of mapped versus surveyed businesses by founding year & AI centrality[11]

Source: Briter Intelligence (2026), African AI Business Survey (2026)

11. Chart presents the founding year of AI businesses that received funding between 2016–2025.

Breaking team size down by operational age shows this pattern taking shape gradually rather than holding constant. Early-stage companies (1–3 years) are overwhelmingly micro (1–10 employees) and small (11–50 employees). Growth-stage companies (4–7 years), the largest cohort in the dataset, shift toward small teams as the dominant category. It's only at the established stage (7+ years) that medium (51–250) and large (250+) teams make up a much bigger share than at any earlier stage.

This shows that digital and AI-first companies tend to have leaner teams than traditional companies by design, but the current market maturity also plays a role. Many of the AI businesses are still at an early or growth stage, and with talent being one of the largest expenses for operations and R&D, most simply aren't mature enough yet to carry larger teams. Talent sourcing itself is also a challenge for many AI businesses, according to the survey, and will be discussed in more depth in Section 5.

Companies that have only been operating for a few years are typically still finding their footing in the market: 46% are generating revenue but remain pre-profit, 22% have launched but are pre-revenue, and 15% have reached profitability. Looking at the data, different compute sourcing strategies persist across every stage, meaning there's no single "winning" architecture that guarantees profitability.

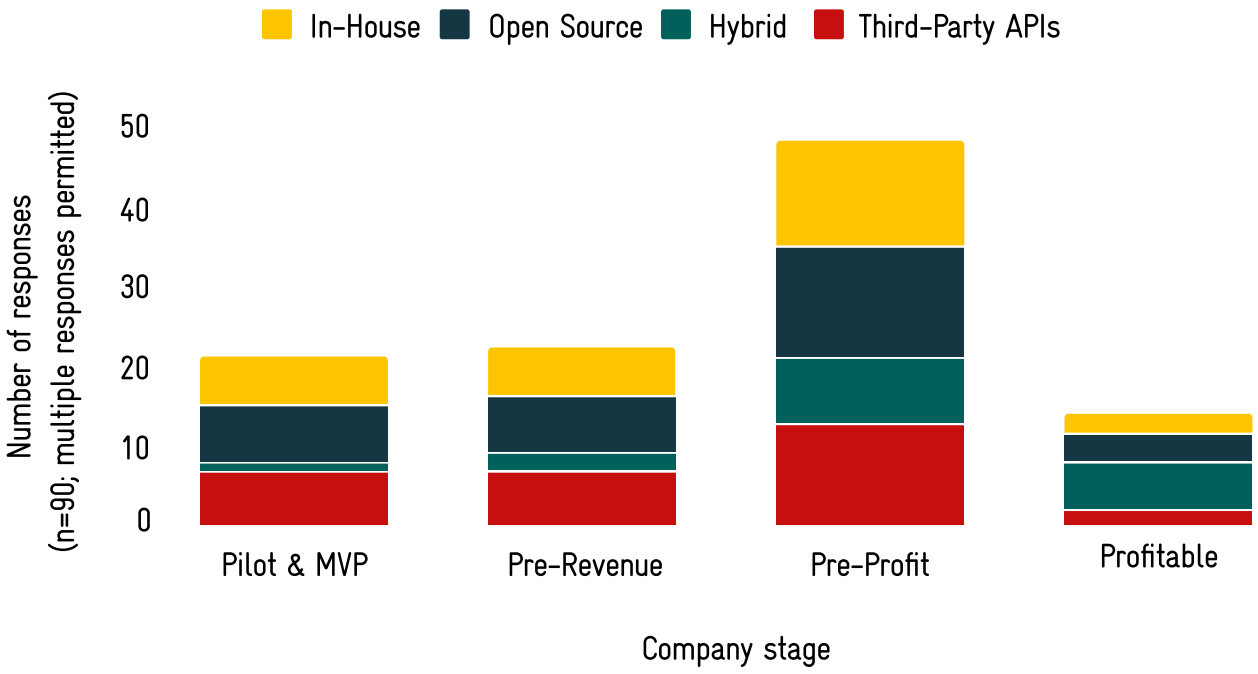


Figure 9: Number of surveyed businesses by revenue stage & AI source[12] Source: African AI Business Survey (2026)

12. Note there was one respondent at the "Ideation" stage but that business did not disclose their AI source (likely they were too early stage to have chosen a particular AI source) so that response is excluded from this.

Customer segmentation

The survey results show that AI businesses across Africa are mainly B2B-oriented, with 88% targeting businesses, 62% serving B2C retail consumers, 44% targeting government (B2G), and 43% serving B2B2C models.

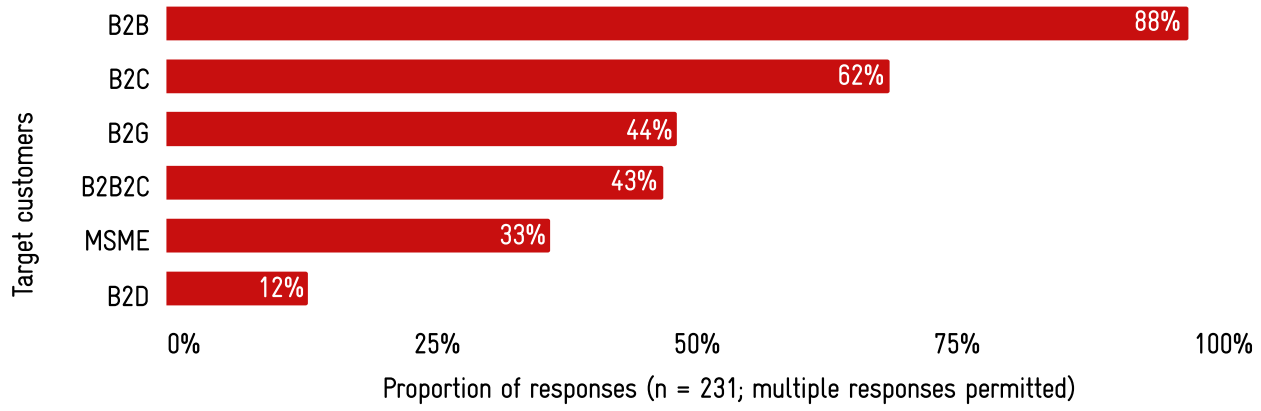


Figure 10: Proportion of surveyed responses by customer type[13]

Source: African AI Business Survey (2026)

Only a handful of companies in the dataset target a single segment exclusively. A few companies that analyse health data for public sector customers or agtech companies that work directly with individual customers have defined a singular group of consumers. But a larger group of surveyed AI businesses offer the core product to multiple consumer segments including individual, business, and government customers, adapting the commercial relationship rather than the technology. For example, Ignitia's weather forecasting reaches smallholder farmers directly via SMS, sells data services to agribusinesses, and works with government agricultural agencies.

The multi-segment pattern likely reflects both the nature of AI infrastructure products, which can sit at multiple layers of a value chain simultaneously, and the practical reality of early-stage revenue diversification in markets where no single buyer segment yet provides reliable volume.

Surveyed AI businesses must also overcome significant barriers to enterprise adoption beyond serving multiple customer segments. Selling AI solutions to businesses and governments often requires educating customers, integrating with legacy systems, and demonstrating value before organisations are willing to change established workflows.

Price

That same institutional buyer base, combined with the ecosystem's youth, directly shapes pricing. The data suggests many businesses are still proving commercial viability (roughly one in five surveyed companies are pre-revenue, and approximately 40% are not yet profitable), reinforcing a broader pattern across the ecosystem where companies are simultaneously building products, educating customers, and establishing viable revenue models in markets where AI purchasing behaviour is still emerging.

13. Note that respondents could choose multiple customers when answering this question in the African AI Business Survey (2026).

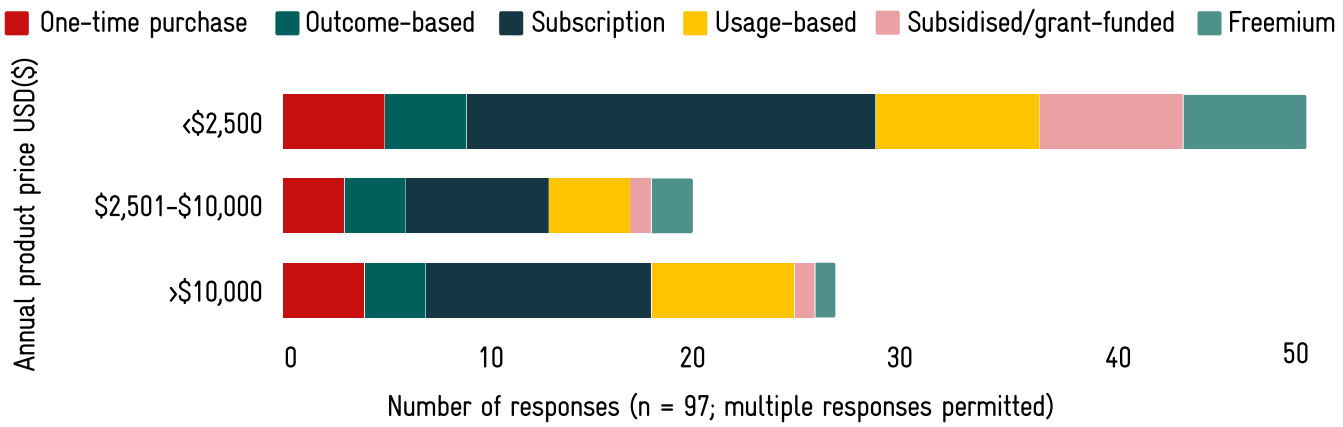


Figure 11: Number of surveyed responses by product price (annual) & revenue model[14]

Source: African AI Business Survey (2026)

The survey shows that subscription pricing is the dominant monetisation model, possibly because it lowers upfront adoption barriers and provides predictable recurring revenue. However, lower-cost AI products are more likely to rely on freemium, grant-supported, or subsidised pricing structures designed to encourage experimentation and adoption in price-sensitive markets. Freemium approaches also allow companies to build user familiarity in markets where AI literacy remains uneven.

By contrast, higher-priced enterprise AI systems increasingly incorporate usage-based, outcome-linked, or one-time implementation pricing. These models are more common among businesses serving institutional clients in sectors such as fintech, logistics, insurance, mobility, and government. In these contexts, AI products are often embedded into mission-critical operations where pricing is linked to transaction volumes, operational savings, compliance outcomes, or infrastructure deployment rather than simple software access.

More than half of surveyed AI businesses price their products below $2,500 annually per customer, which is equivalent to roughly $208 per month. For small businesses in Africa, $208 a month competes directly with core operating expenditures such as internet connectivity, fuel for backup generators, or staff salaries.[15] Research shows that many businesses operate on thin margins, with average turnover for smaller enterprises often below $10,000 annually.[16] This pricing sensitivity helps explain why subscription models dominate and why many AI companies continue to rely on freemium, subsidised, grant-supported, or staggered pricing structures to encourage adoption. **At the same time, the cost base for AI companies remains globally priced. GPU compute, cloud infrastructure, cybersecurity tooling, and foundational model APIs are largely denominated in USD and priced similarly to American or European markets. This creates a structural asymmetry for surveyed African AI businesses: they sell into lower purchasing-power environments while absorbing globally benchmarked infrastructure costs, compressing margins even as adoption grows.**

14. Note that respondents could choose multiple revenue models when answering this question in the African AI Business Survey (2026).
15. MOHAC Africa (2026)
16. MOHAC Africa (2026)

Company Spotlight



The Awareness Company

Scaling operational AI through enterprise adoption

HQ country



South Africa

Years of Operation	Sector(s)	Operational Countries	AI Centrality
7	Mining, Real Estate & Infrastructure	South Africa, Botswana, Mozambique	AI-native

The Awareness Company is a South African AI company that develops HYDRA, an operational intelligence platform that combines data from enterprise systems, sensors, vehicles, cameras, mobile applications, and messaging platforms to provide organisations with real-time operational visibility. The company builds AI for the physical world, where work happens across sites, assets and people rather than inside a single software system. It serves sectors including mining, campus and precinct operations, and industrial and commercial real estate, using proprietary AI models to turn fragmented operational data into decisions that hold up across complex physical environments.

Its enterprise customers recognise the potential of AI, but AI adoption often stalls because implementation requires both technical investment and organisational change. Many organisations lack the digital infrastructure needed to generate continuous, high-quality operational data. This led The Awareness Company to first help clients install monitoring equipment before AI can deliver value to these businesses. Lengthy procurement cycles and high upfront software costs also cause many businesses to be hesitant to commit to large AI investments.

Rather than relying on traditional enterprise software licensing, the company has shifted toward a subscription-based software model that lowers initial costs and allows customers to experience AI value incrementally. This has reduced the financial risk of adoption while giving organisations time to integrate AI into existing workflows before making larger commitments.

> “AI startups have to break through the barriers to work with enterprises who may already have existing partners or take a cautionary approach of ‘assessing now, deploy later’. So startups need to show how deploying AI services in a more agile way can improve their operations.
>
> — **Priaash Ramadeen, Co-Founder**

Surveyed African AI businesses are testing a broad range of customer segments, with most servicing more than one. Companies don’t abandon early architectural choices so much as build on top of them, with hybrid models becoming dominant at the growth stage. Pricing and customer base remain institutionally oriented (B2B/B2G) that builds a more constant consumer base that helps AI businesses build a business case, especially at the face of high costs of AI inputs that are globally priced. The next section turns to the capital behind these businesses: who is funding African AI, how much capital companies are accessing, and how financing is shaping their ability to scale.

Section 4: Funding AI businesses in Africa

Key points

- Funding remains concentrated among older AI companies, while most newer surveyed AI businesses are either bootstrapped or have raised less than $500K.
- Investor composition evolves with revenue: angels are present throughout, while companies raising $1M–$10M attract a more diversified mix of local and international venture capital (VC), public sector funders, corporate investors, and grants.
- Global expansion, higher funding levels, and profitability are strongly correlated, although the direction of causality cannot be determined from the data.

For surveyed African AI businesses, commercial traction does not necessarily translate into financial security. Access to capital remains uneven, with companies largely concentrated in the earliest stages of funding and a relatively small number reaching later rounds or international scale. This section examines where AI businesses are in their financing journeys, who is providing capital, how much they are raising, and what founders say they need from investors to grow.

Funding structure

When it comes to funding, investment in AI businesses picked up in 2021 and reached its peak in 2023, tracking the global cycle of AI investment. Companies raised close to $500M during this transition from the pre-AI boom to rapid adoption of AI due to GenAI. Although funding volume has declined in recent years, the number of deals and funded companies nevertheless continue to rise, signalling that there is continued investor interest in AI businesses, despite smaller ticket sizes.

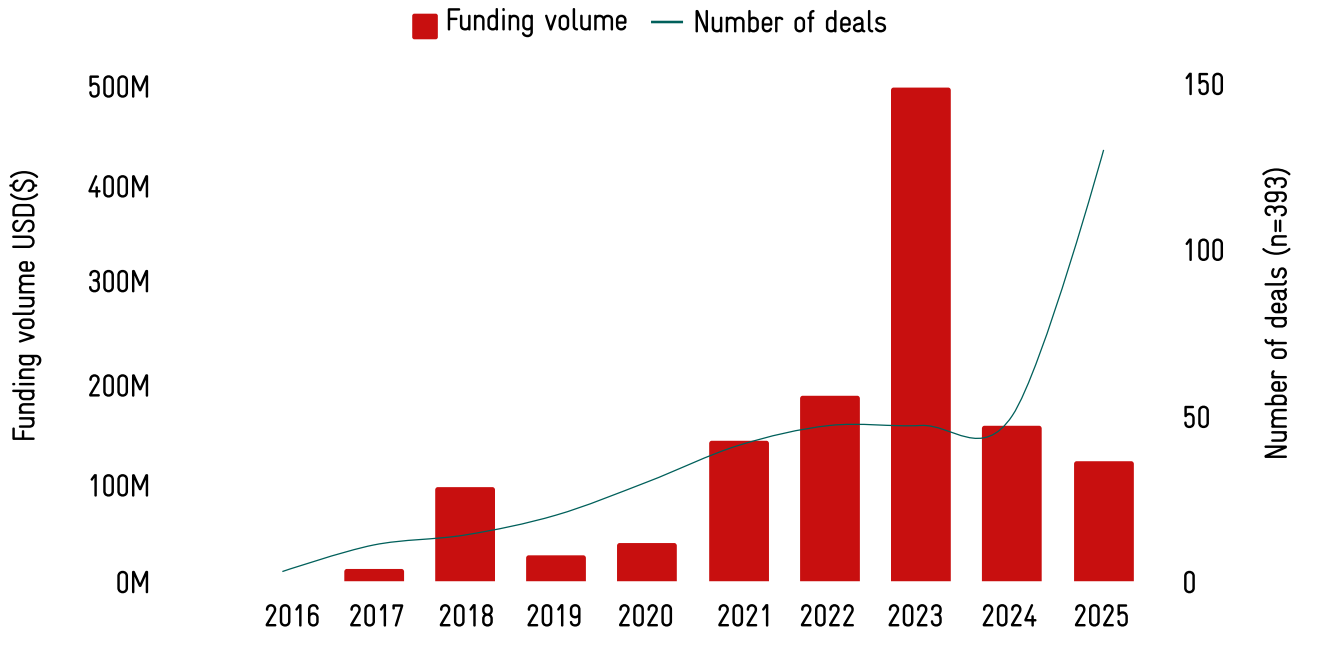


Figure 12: Number of mapped businesses by funding volume & number of deals

Source: Briter Intelligence (2026)

This pattern echoes something visible in the survey data too: funding remains concentrated among pre-2020 companies even as the population of AI businesses has grown younger overall, meaning newer, AI-native cohorts are entering a funding environment shaped disproportionately by an older generation of raises. The survey's funding stage distribution bears this out at the individual-company level: roughly 30% of companies are entirely bootstrapped, a quarter have raised under $500K, just under a quarter have raised $1M-$10M, only one company has raised $10-$50M, and less than 10% sit in the $500K-$1M transitional range. Older companies in the cohort have generally raised more than early-stage ones, but some older companies remain bootstrapped or raising minimally.

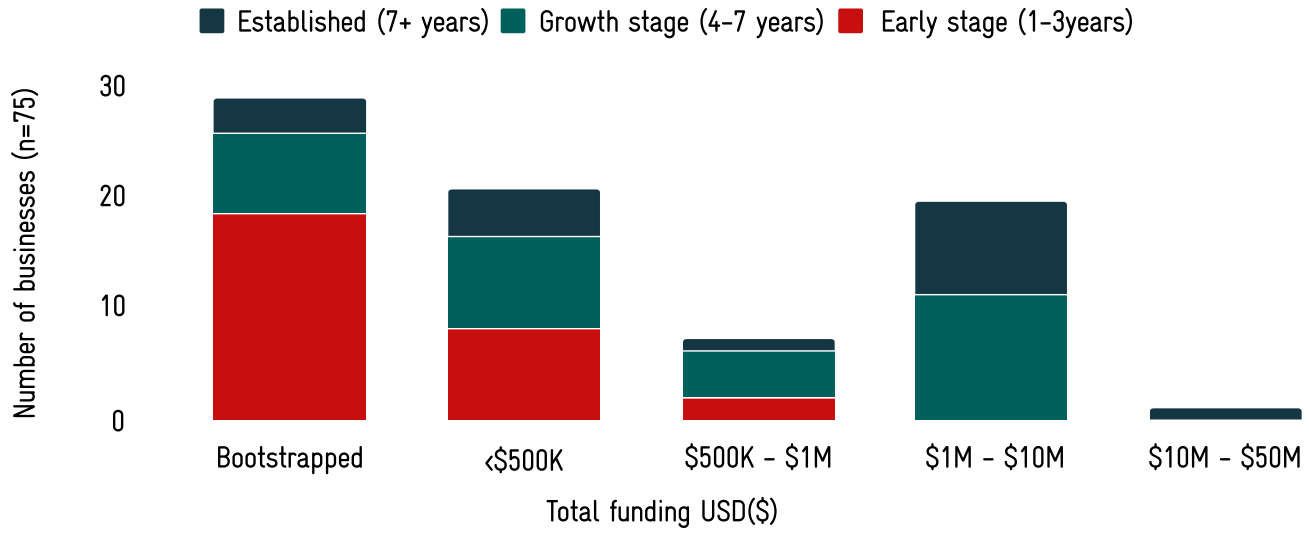


Figure 13: Number of surveyed businesses by total funding & operational age[17]

Source: African AI Business Survey (2026)

Regardless of sectors, revenue, and geography of companies, accessing working capital and patient capital was considered as a scaling priority for many of the surveyed AI businesses. When asked to share what can unlock the company's growth, many responses mentioned accessing capital. Examples of anonymised responses from the survey are:

> "Access to capital and affordable compute infrastructure would unlock our ability to scale rapidly."

> "Access to patient, mission-aligned capital from investors who understand the African education landscape would be the single greatest unlock for our growth"

> "Access to funding to develop our R&D that will improve the quality of our data that the AI engine trains on."

> "Access to funding and opportunities to travel for international AI conferences."

This funding gap likely explains why so many surveyed AI businesses cite funding or subsidies as a top policy priority. But the qualitative data adds an important qualifier: founders aren't simply asking for more capital, they're asking for capital that understands the operating environment. Patient, mission-aligned investors are especially sought after among health, education, and agriculture-focused companies, where the constraint isn't just volume, it's investor literacy about local regulatory timelines, currency exposure, and the longer trust-building cycles B2B and B2G sales require in these markets.

17. Note that 10 respondents that did not respond to this question in the African AI Business Survey (2026) was excluded from this analysis.

This same funding-stage pattern shapes how companies source their AI models. At the bootstrapped and sub-$500K stages, compute sourcing is relatively balanced: companies use whatever's most accessible. At $500K-$1M, companies have enough capital to start thinking about infrastructure but not enough to go fully proprietary, making hybrid a natural middle path. In the $1M-$10M band, hybrid and in-house dominate as the unit economics of third-party APIs start to hurt. A company serving thousands of daily users can rack up $20K-$50K a month in API costs, making infrastructure investment economically rational.[18]

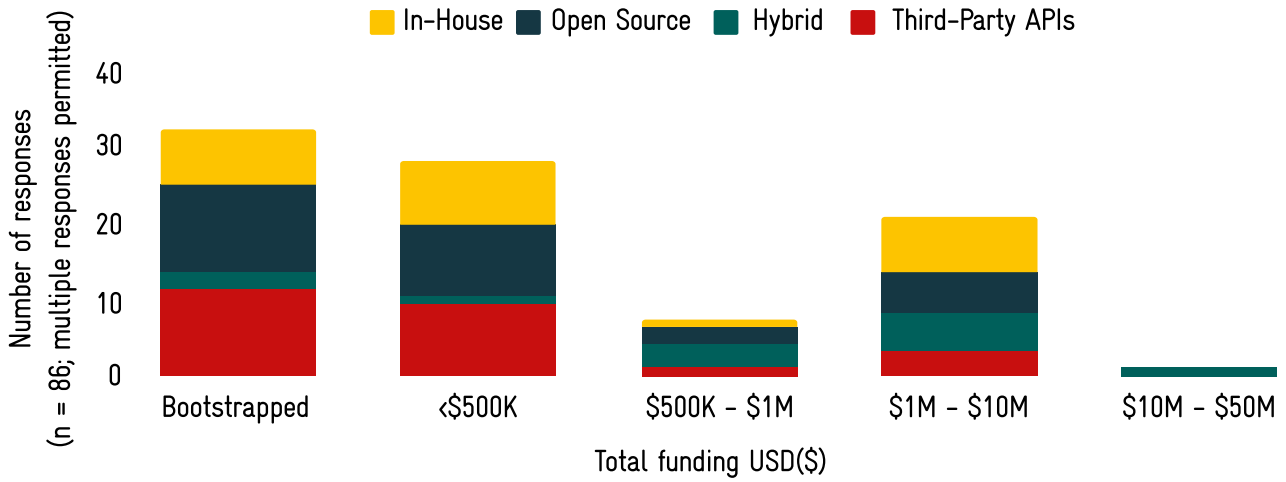


Figure 14: Number of surveyed responses by total funding & AI source[19] Source: African AI Business Survey (2026)

Technical debt reinforces this progression. Companies that start with third-party APIs at the pre-seed stage often find it prohibitively expensive to migrate to hybrid or open source later, creating a path dependency where architectural choices made at founding driven by budget, talent, and time-to-market constraints persist even as circumstances change and a more cost-effective architecture becomes available.

Investor type

Looking at funding types, angels show up at every stage, a sign of how central they are to the funding stack for surveyed AI businesses in Africa. Local and international VCs, unsurprisingly, are key to helping companies scale. This section analyses investors that are involved in companies by their total fundraised to date. The list of investors is cumulative to date, and should be considered as the consortium and syndicate of funders that show up on a business' cap table across growth stages.

This report groups funding raised into five bands that correspond roughly with stages of companies: "bootstrapped" group representing very early stage businesses with one or two key customers to test out their offerings; "under $500K" are early stage businesses with tested products and services that have managed to fundraise with some early backers; the "$500K-$1M" band represents businesses that are transitioning from early stage to growth stage but this is also the stage where most African businesses see a funding bottleneck due to the lack of instruments and funders catering to this range; the "$1M-$10M" group shows companies that are in the growth stage, raising funding with institutional investors and others; and lastly, the "$10M-$50M" group represents growth and scaling stage businesses with longer-term backers.

18. Mullany (2026)
19. Note that respondents could choose multiple AI sources when answering this question in the African AI Business Survey (2026).

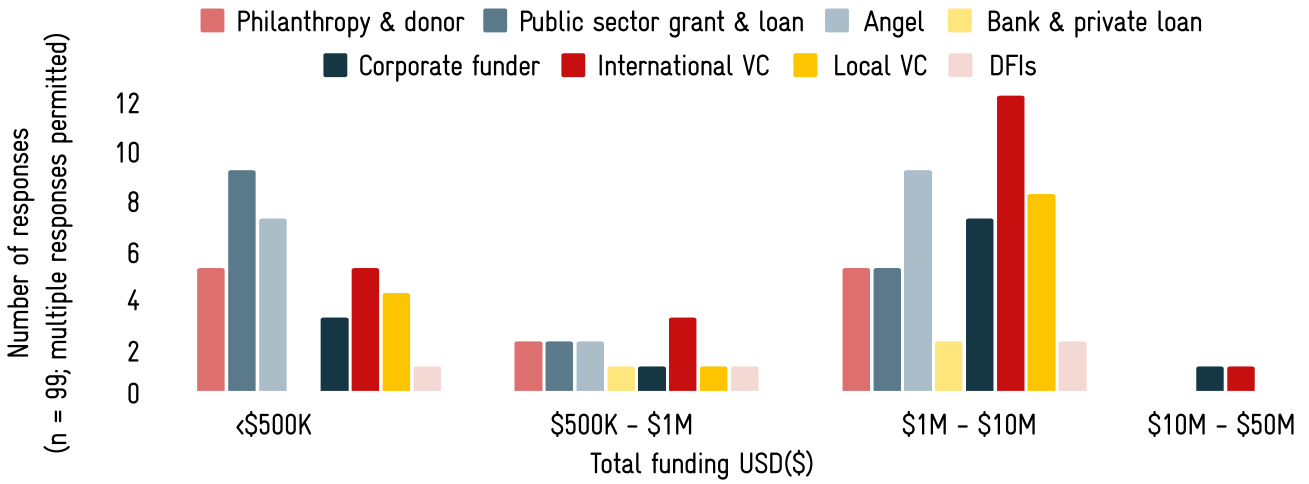


Figure 15: Number of surveyed responses by investor type and total funding raised to date[20]

Source: African AI Business Survey (2026)

In the sub-$500K stage, public sector grant & loan funding is the largest category while local VC, and corporate funders are also present alongside angels. This suggests that companies at this stage are piecing together capital from multiple sources, particularly non-dilutive or semi-concessional funding mechanisms that help founders achieve early traction and validation.

The $500K-$1M band shows a narrower investor base overall, with international VC playing the most visible role. Funding is minimal at this stage, and colloquially known as "the missing middle" where capital concentrates on early-stage companies and businesses that have shown profitability but bridging that gap is often difficult.

The $1M-$10M band shows the most diversified investor base: international VC, public sector grant & loan, local VC, corporate funders, and angels all present in significant numbers. This suggests that companies reaching this funding threshold have successfully de-risked enough to attract institutional capital, but are still layering multiple sources rather than relying on a single lead investor. The continued presence of public sector funding even at this stage is notable and indicates that grants and concessional finance remain important as companies scale, not just at inception.

The $10M+ band shows a shift toward corporate capital, with international VC still present. At this scale, companies are likely engaging strategic corporate investors who provide not just capital but distribution partnerships and enterprise customer access.

The qualitative comments from survey respondents reinforce what the numbers suggest: fundraising in the African AI space is challenging. As one founder noted, "accessing funding for AI startups in Africa is challenging due to investor skepticism, long decision cycles, and a preference for traction over innovation." Another stated plainly: "It has not been easy convincing people about the use of AI and the benefits thereof."

What founders appear to want is not simply access to more capital, but access to fit-for-purpose investments. AI business founders need investors who understand that B2G sales cycles in African markets are extremely long[21], that

20. Note that respondents could choose multiple investors when answering this question in the African AI Business Survey (2026). Additionally, "Bootstrapped" as a category was removed since bootstrapped companies do not have any investors but are rather self-funded. There were 28 bootstrapped companies in this dataset (33%).
21. SEJunction (2026)

currency devaluation is a structural operating risk, that infrastructure costs are 2-3x higher than in developed markets[22], and that product-market fit in these contexts looks different than it does in Silicon Valley. The capital exists; the patient, informed capital that can support the specific growth trajectories of African AI companies remains scarce.

AI businesses operational only in Africa versus those operational beyond Africa

A final insight into funding comes from looking at companies that only operate regionally within Africa versus those that operate internationally. This distinction is important because geographic reach appears closely linked to both commercial scale and capital access throughout the dataset.

Among profitable companies, 60% operate globally compared to just 40% only in Africa; at the pilot stage, that ratio flips to 83% operational only in Africa versus 17% beyond Africa. The inflection point lands at the pre-profit stage, where the split is nearly 50-50. This is the moment companies that have reached revenue but not yet profitability face a choice between consolidating existing markets or expanding to reach profitable scale.

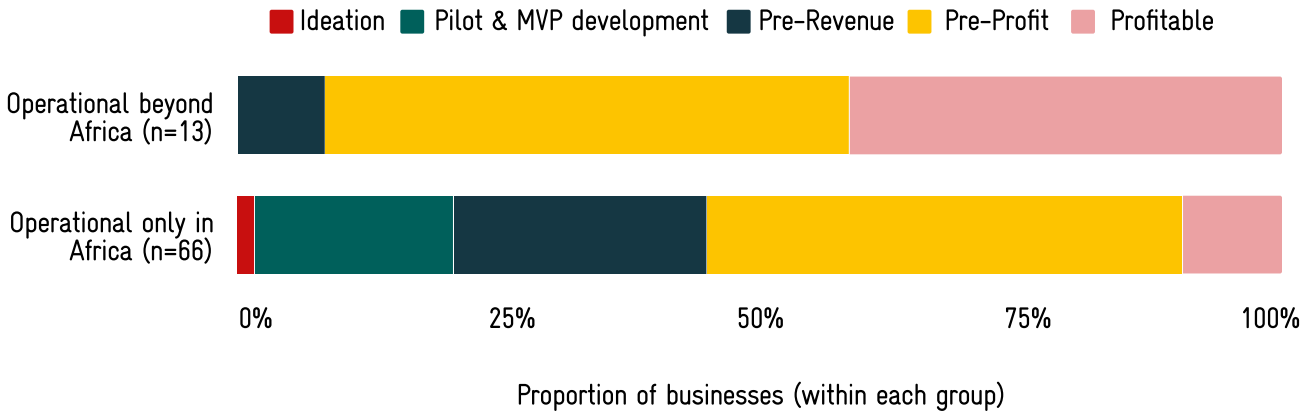


Figure 16: Proportion of surveyed businesses by revenue stage and regional group[23]

Source: African AI Business Survey (2026)

Regional and global expansion of surveyed AI businesses is related to accessing growth capital. At lower funding stages, most companies stay regionally focused: roughly 65% of bootstrapped companies and 75% of those in the sub-$500K band operate primarily within Africa. Among companies in the $1M-$10M range, that flips: roughly 75% operate beyond Africa. The inflection point again appears as companies move past early-stage financing and begin scaling across multiple markets, suggesting the profitability/geography link and the funding/geography link are two faces of the same underlying dynamic rather than two separate findings.

This is partially explained by an emerging pattern of founders relocating their headquarters to jurisdictions with more favourable regulatory frameworks. Some interviewees pointed out that cities in the Middle East such as Dubai and Riyadh are a common destination for Northern African founders seeking easier business facilitation and access to Gulf capital. This is worth further

22. OECD (2025)
23. Note that these figures reflect responses to this specific question and therefore do not represent the full 85 survey respondents. Of those who provided a response, 13 reported operating both within and beyond Africa, while 66 reported operating exclusively within Africa. Any analysis of companies operating both within and beyond Africa should therefore be interpreted in the context of this lower response count.

study as it represents a form of regulatory and commercial brain drain from African markets that undermines the continent's long-term AI ecosystem development, even as the companies involved may continue to employ local talent and serve local markets. Nevertheless, activities such as these help to explain why surveyed AI businesses with global presence have often been more profitable than their counterparts operational only in Africa.

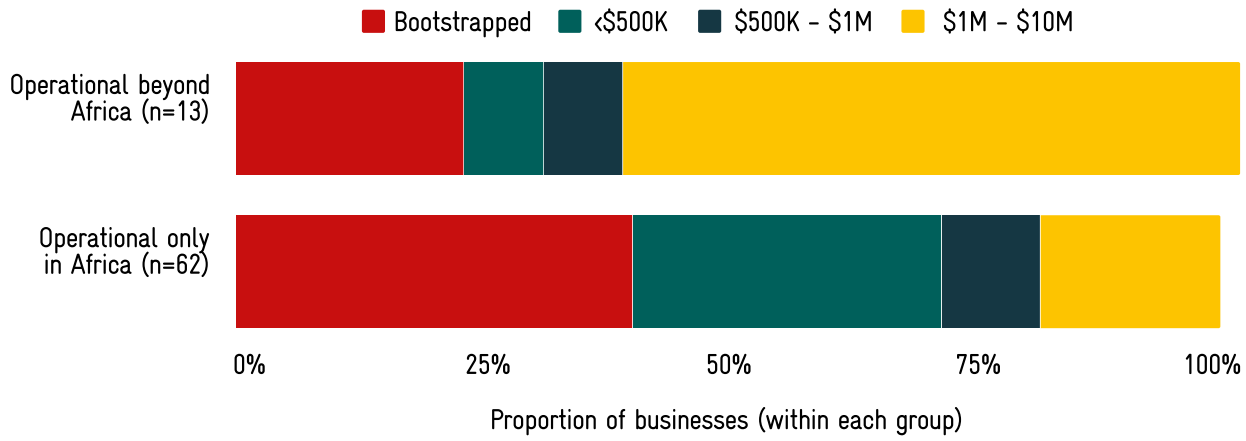


Figure 17: Proportion of surveyed businesses by total funding and regional groups[24]

Source: African AI Business Survey (2026)

This points to a structural feature of surveyed AI businesses that distinguishes them from traditional enterprises: they can scale across borders more easily[25]. Unlike retail chains, manufacturing, or telecoms (which require physical infrastructure in each new market), AI products can often expand with comparatively modest investment once the core technology is built. Deploying in a new country primarily requires localisation, regulatory compliance, and go-to-market execution rather than rebuilding the technology stack.

That said, the cross-border scale isn't free. It requires upfront investment in GPU and AI infrastructure and needs to factor in the dynamic and highly variable compute scaling costs. Companies also need a business model and product already proven in a home market before expansion is viable as cross-border scale compounds an unproven model's risks rather than fixing them. Skilladder, a Nigerian AI-native HR and talent tech company, has leaned on global-scale partners like Mastercard Foundation and GIZ to help validate its workstream in one market before the kind of cross-border expansion described above becomes a realistic next step.

As with the profitability relationship, it is difficult to understand if companies that operate beyond Africa raise better or if capital is what drives expansion: companies operating internationally are substantially more represented in higher funding brackets, but the data can't determine whether they raise more because they expanded, or expanded because capital access enabled it. Qualitative evidence points to both forces reinforcing each other. One Western African company in our survey which operates across multiple African and international countries described a "pull" model: profitability in the home market created the credibility and cash flow to expand, following institutional insurance clients into new territories. Ignitia, Sweden-founded and operating across

24. Note that these figures reflect responses to this specific question and therefore do not represent the full 85 survey respondents. Of those who provided a response, 13 reported operating both within and beyond Africa, while 66 reported operating exclusively within Africa. Note that for this question, some businesses operating exclusively within Africa did not provide a response when asked about their funding. Any analysis of companies operating both within and beyond Africa should therefore be interpreted in the context of this lower response count.
25. MIT Sloan Management Review (2026)

18 African countries plus Brazil, Colombia, and Indonesia, described the opposite "push" model, where satellite-dependent forecasting made geographic expansion relatively inexpensive and profitability required aggregating demand across markets to justify fixed model-development costs.

The companies operational only in Africa that do reach larger funding thresholds are likely benefiting from large domestic markets (Nigeria, South Africa, Kenya) or from sector dynamics that allow substantial scale within a single market. **The point isn't that international expansion is inherently superior; it's that scale, market access, and financing are tightly interconnected in this ecosystem, at both the revenue-outcome level and the capital-input level.**

African AI companies face a financing challenge that is as much about capital quality as capital quantity: founders consistently emphasise the need for patient, locally informed investors who understand the realities of African markets. Most surveyed AI businesses remain in the earliest funding stages, limiting their ability to invest in infrastructure, talent, and proprietary AI capabilities. Companies operating only within Africa can become trapped in a reinforcing cycle where limited capital constrains expansion, and limited geographic scale reduces access to the larger pools of funding needed to grow. The next section looks beyond capital to the wider ecosystem bottlenecks holding these businesses back, from infrastructure and cloud costs to talent, data, and customer adoption.

Section 5: Ecosystem bottlenecks and infrastructure challenge

Key points

- 65% of businesses cite customer trust/literacy as the top barrier to scaling.
- 61% cite high cloud costs as the top infrastructure bottleneck.
- 65% of companies listed cloud/compute cost as their largest spending category in the R&D process.
- Talent scarcity (especially senior AI research roles) has pushed companies toward internal training as a default strategy.

Even when capital is available, surveyed African AI businesses face structural constraints that cannot be solved through funding alone. Infrastructure remains expensive and uneven, specialised talent is scarce, and customers often lack the trust or technical literacy needed to adopt AI at scale. This section explores the operational bottlenecks founders encounter, from cloud and compute costs to talent, data, and customer readiness, and the strategies businesses are using to work around them.

Scaling priorities

The top scaling priorities identified from the survey reveal that AI businesses across Africa are mainly in the validation stage rather than scaling stage. 31% and 18% of surveyed AI businesses responded that pre-scaling activities such as "growing user/customer base" and "achieving product-market fit" were scaling priorities. 20% of surveyed AI businesses are prioritising increasing revenue and 15% cite "expanding to new markets" as a top priority, which suggests that even companies operating in multiple countries are still consolidating their position in existing markets rather than confidently expanding. This is consistent with the data that close to half of AI businesses are revenue-generating but pre-profit, meaning they have customers but haven't yet generated positive cashflow for the longer run.

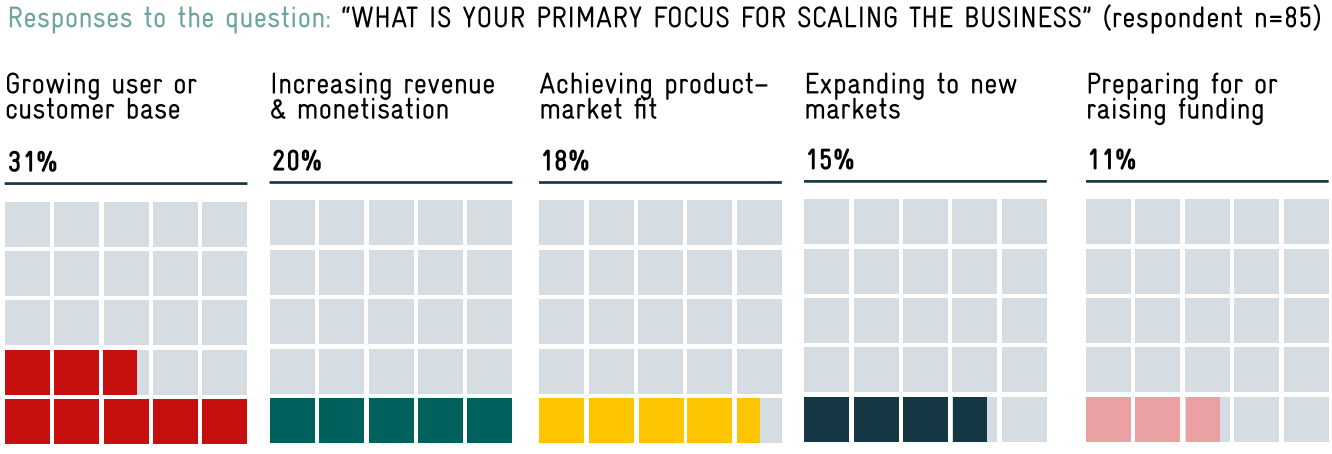


Figure 18: Proportion of surveyed responses by scaling priorities[26]

Source: African AI Business Survey (2026)

26. Note that respondents could choose multiple priorities when answering this question in the African AI Business Survey (2026).

Growing user base and increasing revenue looks different across the sectors and markets given different conditions affecting surveyed AI businesses. Based on the survey responses and direct engagements with AI businesses, the following scaling priorities emerge in key sectors:

Agriculture & agtech - Strengthening monetisation

AI-enabled products in agriculture & agtech can reach a large pool of potential customers, but the sector carries high development costs: onboarding often requires field agents, and data collection is expensive because there's little publicly available data to draw on. This is also a sector with low willingness to pay with a B2C model, so many agtech AI companies are still figuring out their business model and monetisation plan. Some companies are leveraging grant funding to provide their services to the smallholder farmers who can benefit the most through the service despite the limiting requirements attached to the grant[27]. Some have diversified revenue strategies to include partnerships with telecommunication providers and expansion into other relevant sectors like logistics to mitigate high development costs[28].

Fintech - Market expansion and increasing revenue

Surveyed fintech AI businesses need to find more revenue sources, expand into new markets, and fundraise for growth regardless of their revenue. Because many fintechs build proprietary technology and sell through B2B channels, they typically invest heavily upfront to build enterprise-grade solutions, then scale through enterprise subscriptions. Growing their subscriber base then helps them recoup that initial investment and fund expansion into new markets. Some of the companies reported they are relying on angel funders to help fund their operations but will be looking for institutional investors once their models are more proven.

SaaS/AI Transition - Growing users and creating product-market-fit

Surveyed AI businesses developing enterprise solutions face longer sales cycles and often need to tailor their products to highly specialised operational requirements. For SaaS play companies, they have to demonstrate that deploying an AI tool now and perfecting the solution together is beneficial[29] and helping clients to increase the quality of data inputs and improve processing to see better results in the AI tools[30].

Health - Strengthening monetisation

The health sector is a highly regulated one with high barriers to data. This makes the cost of developing AI businesses high in the sector, and companies need to be creative to increase their relevance and affordability. Some companies, as similar to agtechs, are working with enterprise partners that will subsidise access to cloud or computing credits and bundling their AI products with other products and services[31].

Scaling barriers

The survey asked AI businesses to name their top barriers to scaling. Customer trust & literacy came out on top, followed by high development & consumer costs. Over a third of respondents also cited integration with legacy systems, long sales cycles, and data availability as primary barriers.

27. Interview with Soil Solutions
28. Interview with Ignitia
29. Interview with The Awareness Company
30. Interview with MPhando
31. Interview with Myltura and Venille AI

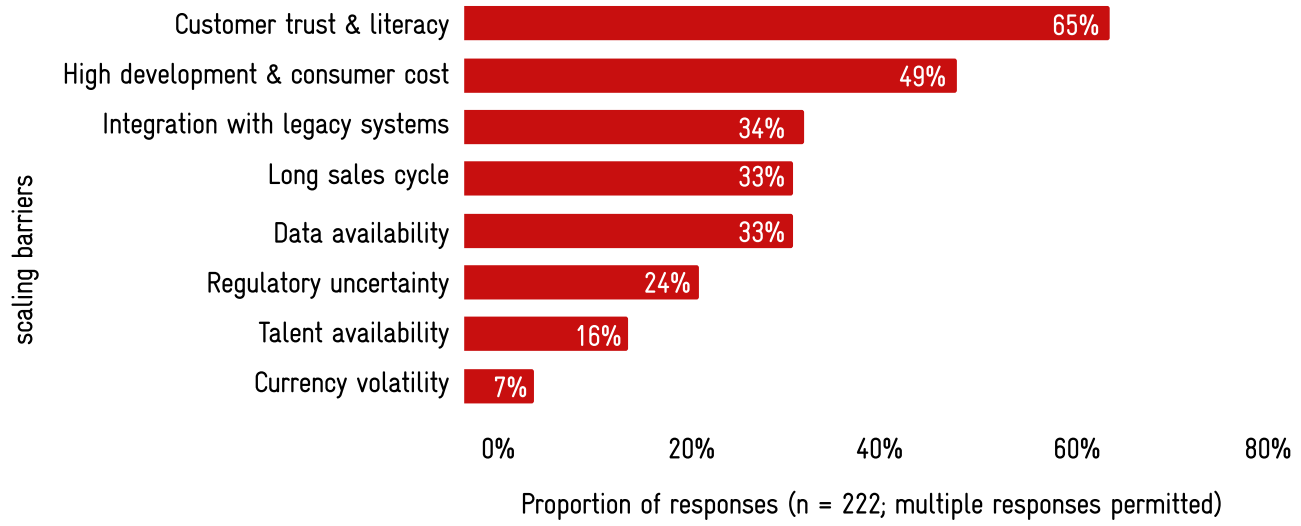


Figure 19: Proportion of surveyed responses by scaling barriers[32]

Source: African AI Business Survey (2026)

The single biggest barrier to scaling is not technology, but market readiness: 65% of companies cite customer trust and literacy as their primary constraint. Partially this is because of the broad definition of what customer trust and literacy can encompass. Interviews with AI businesses inform three key areas of customer trust and literacy that bars AI adoption in the market:

1 Creating consumer behavioural change

AI businesses need to encourage adoption of new technology and tools for institutions and businesses, away from familiar tools. This means spending more time and resources with each customer to drive behavioural change. For example, The Awareness Company, a South African AI business, reports that they have to educate their potential customers on the explicit benefits of using AI tools compared to existing tools like spreadsheets.

2 Creating buy-in about the accuracy of AI technology

This customer scepticism is linked to the systemic issue that many AI models are trained on data that exclude locally relevant African contexts[33]. The less accurate or relevant AI products become to potential customers, the higher the barrier to adopting the technology. MyItura, a Nigerian health tech business profiled later in this report, offers a concrete example: its diagnostic AI produces hallucinations due to being trained on foreign datasets, and this introduces additional cost and effort for the company to create buy-in and to sharpen their model, beyond what AI businesses would need to do in European or American markets.

3 Managing expectations and data gaps

AI businesses in Africa also face high expectations that an AI tool should fix persisting issues in a short time, while building good data and bespoke AI solutions can take a long period of time to develop. Unreliable access to data to build good AI products also makes the R&D timelines longer for AI businesses. For example, MPhando, a Zambian B2B AI consulting firm reports that low quality data input resulting from existing manual data input practices of the client impacted the quality of the output. This can ultimately erode the client's trust in the system.

32. Note that respondents could choose multiple challenges when answering this question in the African AI Business Survey (2026).
33. Adebara (2025)

For consumer-facing surveyed AI businesses, adoption depends not only on building accurate AI systems but also on helping users understand, trust, and confidently engage with them. Venille illustrates how they have addressed this challenge through product design, education, and community engagement.

Company Spotlight

Venille

Building trust to scale AI-driven tool for women's health

HQ country: Nigeria

Years of Operation	Sector(s)	Operational Country	AI Centrality
4	Software, Health	Nigeria	AI-enabled

Venille is a Nigerian femtech business founded to address period poverty through affordable biodegradable sanitary products. As the company expanded into underserved communities, it realised that limited access to menstrual products was only part of the challenge. Many women and girls also lacked access to reliable reproductive health information, prompting the company to launch Venille AI, a platform that tracks menstrual cycles, offers educational resources, and an AI-powered chatbot that delivers personalised menstrual health guidance.

Venille serves individual consumers, making trust central to product adoption. Many users remain unfamiliar with AI or are hesitant to rely on AI-generated health advice, particularly for sensitive health questions. The company addresses this by investing in community demonstrations, user education, transparent communication, and intuitive product design to build confidence in the platform. It also faces the added challenge of supporting multiple local languages while expanding across Nigeria's diverse linguistic landscape. Venille navigates the barrier of translating complex health information into over 30 indigenous languages by focusing on its initial English rollout while actively working to make the AI available in multiple local dialects to ensure broader accessibility over time.

Beyond language, the business must navigate significant data gaps and high infrastructure costs. Global language models often miss the cultural context and realities of rural African women. Venille solves this by fine-tuning open source models using anonymised data collected from its 3,500 active Nigerian users. Finally, the company relies on AWS business credits to manage expensive cloud computing costs while building towards a profitable premium subscription model.

> "Building Venille AI gave us the opportunity to make health information more accessible and personalised in a more scalable way and to our existing users"
>
> — Esther Olalude, CEO and Founder

High development costs are the second major scaling barrier for surveyed African AI businesses. Interviews suggest that many businesses spend a disproportionate amount of early-stage capital addressing foundational infrastructure gaps rather than building differentiated products. Data availability further compounds this challenge, creating a reinforcing cycle: weak data environments increase development costs and increase R&D timelines, while prolonged development cycles make it harder for companies to generate revenue quickly enough to sustain operations.

Long sales cycles also represent a major obstacle to scale, particularly for companies operating in B2B and B2G markets, which is the majority of this dataset. Integration with legacy systems means that AI companies frequently need to invest additional resources in systems integration and workflow adaptation before their products can demonstrate value. These long commercial cycles also interact directly with the trust barrier that businesses mentioned. Taken together, these findings suggest that the barriers surveyed African AI businesses are facing are not solely technical; they are equally about onboarding institutional users and the market environment. Companies are operating in environments where customer trust, digitisation gaps, infrastructure costs, and procurement systems all shape the pace at which products move from experimentation to sustainable scale.

Access to data was mentioned as a large need for many surveyed AI businesses across sectors. Most companies lack access to reliable data such as crop or soil-level data or high-quality aerial imagery at a national and regional level. Some anonymised feedback from the survey on data needs are:

> "(We can scale with) Access to government data and or more partnerships with government to improve efficiencies in their own systems."

> "(We can scale with) Access to structured, interoperable datasets that link real-world activity to financial outcomes would most unlock our ability to scale AI-driven risk systems."

Talent deficiency

The backgrounds of founders of these AI businesses show the majority have technical, business, or finance degrees. Technical degree founders account for the largest share of degree distribution ahead of other disciplines, showing that the AI business ecosystem is strongly driven by individuals trained in engineering, computer science, ICT, and other technical fields. Business and finance degree founders also have a high representation, indicating that commercial, financial, and managerial expertise is also an important driver of AI-driven businesses.

Over 57% of founders received their education within Africa. Among founders with technical backgrounds, roughly two thirds studied in Africa, in comparison to those with a business background who have studied within and outside Africa equally. The small proportion of founders with social and creative degrees have primarily studied outside of Africa, suggesting that these disciplines rely on more international exposure and networks.

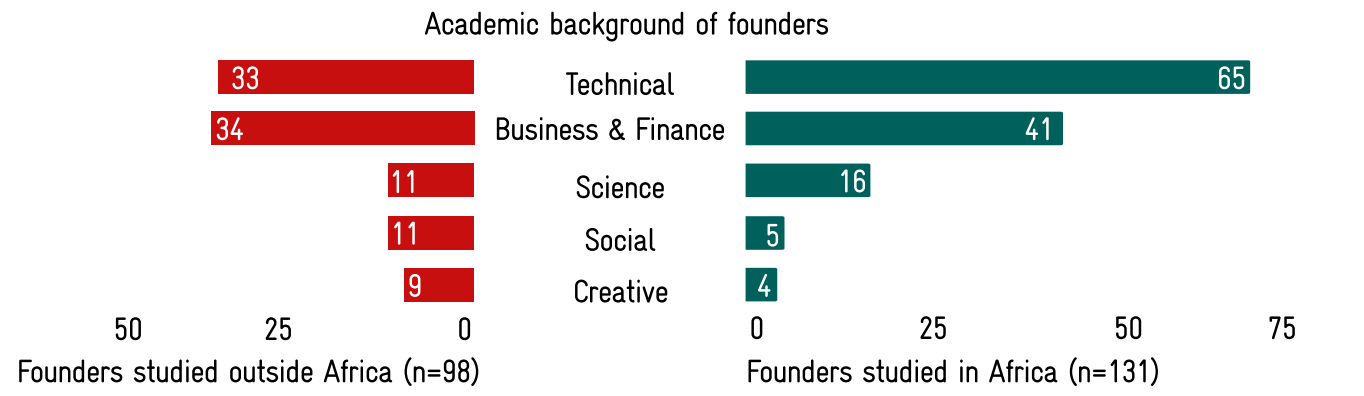


Figure 20: Number of founders in mapped dataset by educational background & location

Source: Briter Intelligence (2026)

Yet, senior AI talent is a binding system constraint. High-level technical roles are facing acute shortages that cannot be easily solved. AI research roles are reported as the hardest to hire, according to 51% of respondents, followed by MLOps/ Infrastructure roles at 33%, and data engineering roles at 23%. Digging deeper, AI businesses report that their primary challenge is the outright limited availability of qualified talent, compounded by salary competition, the pull of international remote opportunities since international businesses can easily outbid local salary structures for top-tier African talents.

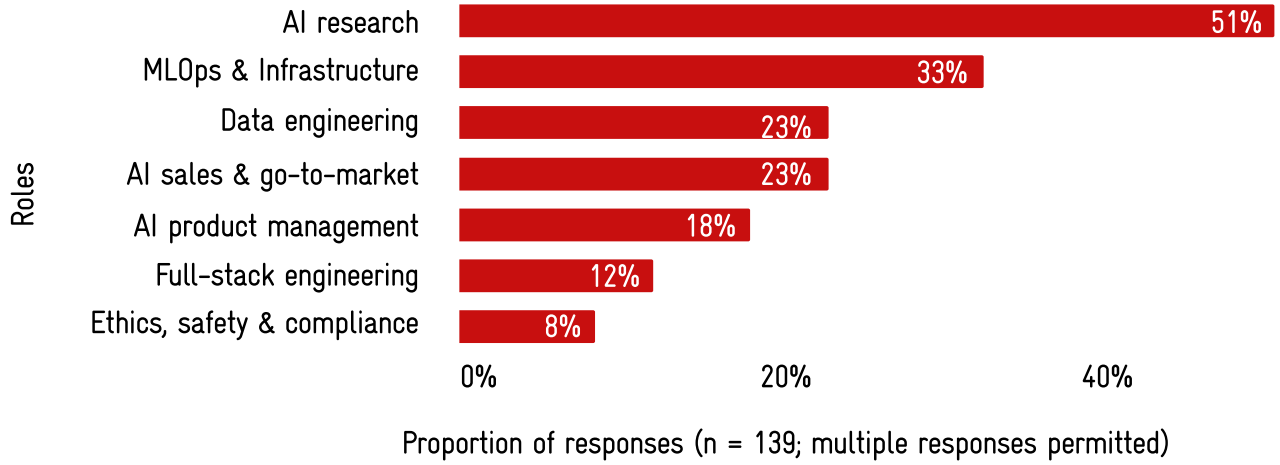


Figure 21: Proportion of surveyed responses by most difficult roles to hire[34]

Source: African AI Business Survey (2026)

Talent struggles are a direct reflection of the continent's tech talent supply chain. Africa accounts for just 1% to 3% of the global AI talent pool, driven by low university enrolment rates (9% across Sub-Saharan Africa compared to a global average of over 40%) and a lack of dedicated AI academic infrastructure.[35] While universities across tech hubs like Nigeria, Kenya, and South Africa are successfully scaling traditional computer science and engineering cohorts, specialised AI degree programes remain exceedingly rare, often restricted to a small handful of competitive postgraduate programes in South Africa.[36] Because specialised AI academic pipelines are highly bottlenecked, African businesses are finding it far more practical to hire from the broader pool of traditional engineering and business graduates and upskill them into adjacent roles like front-end engineering and AI product management.

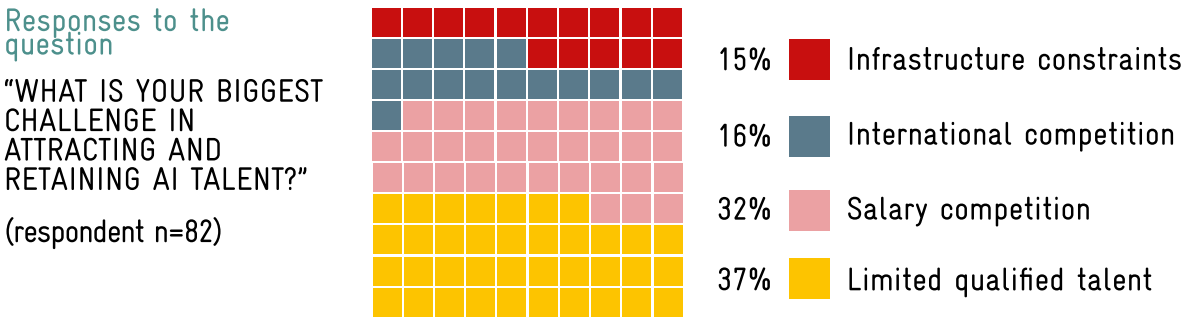


Figure 22: Proportion of surveyed businesses by primary AI talent challenges[37]

Source: African AI Business Survey (2026)

34. Note that respondents could choose multiple roles when answering this question in the African AI Business Survey (2026).
35. Businessday Tech & PwC Africa (2026)
36. UNESCO Institute for Statistics (2026)
37. Note that the chart reflects responses from 82 respondents. Three respondents selected "Other" and provided qualitative responses, which are not reflected in the chart.

As a response to the shortage of talent, surveyed AI businesses are increasingly adopting hybrid talent strategies that combine selective international recruitment for senior technical leadership with sustained investment in developing local engineers. Danaya's experience illustrates how these talent constraints are influencing hiring decisions and long-term capability building.

Company Spotlight

Danaya

Leveraging international talent pool to resolve bottlenecks to scaling

HQ country



Côte d'Ivoire

Years of Operation	Sector	Operational Countries	AI Centrality
3	Regulatory Tech	Côte d'Ivoire, Senegal, Benin, Togo, Burkina Faso	AI-enabled

Danaya is a regtech business based in Côte d'Ivoire that helps financial institutions and other businesses automate their Know Your Customer (KYC), Know Your Business (KYB) and Anti-Money Laundering and Countering the Financing of Terrorism (AML/CFT) compliance processes. Its platform combines artificial intelligence with access to trusted government and private data sources to verify individuals and businesses and assess compliance risks in real time. It integrates Optical Character Recognition (OCR), facial recognition and liveness detection, as well as screening against sanctions lists, Politically Exposed Persons (PEPs) and adverse media. To facilitate adoption, Danaya develops simple, low-friction solutions designed to integrate into the existing processes of financial and other institutions. Its application enables agents to capture an identity document, automatically extract the relevant information and verify it against multiple data sources, making compliance processes faster, more reliable and more secure.

Danaya currently performs verifications in Côte d'Ivoire and is expanding its operations into other Francophone African markets, such as Senegal, Benin, Togo and Burkina Faso. This growth is driving an increasing need for more specialised and senior technical expertise. While Côte d'Ivoire has a growing pool of talented software engineers and data professionals, Danaya complements these local capabilities with seasoned professionals bringing international experience in specialised technology fields. As part of this approach, Danaya recruited an experienced African technology leader with a strong international track record (with work experience in France) as Chief Technology Officer (CTO). His role is to lead Danaya's technology strategy and development, strengthen its artificial intelligence capabilities, and foster knowledge transfer and skills development within the local team.

At the same time, Danaya is investing in the development of a local pool of specialised talent by recruiting young Ivorian engineers and graduates and strengthening their skills in areas such as GenAI, computer vision and machine learning. This approach enables Danaya to combine local expertise with international experience, build capabilities directly tailored to its products and to the realities of African markets, and contribute to the development of Côte d'Ivoire's technology ecosystem and AI talent pool.

> At Danaya, we combine artificial intelligence with access to trusted government and private databases to make KYC, KYB and AML/CFT processes faster, more reliable and more secure. Our challenge is to bring these advanced capabilities into financial institutions without disrupting their existing systems, while making integration as simple as possible.
>
> — **Gauthier de Gerlache, CEO and Co-Founder**

The case study illustrates that retaining senior AI talent may require more than competitive salaries; there is a need to create an ecosystem where experienced professionals can build and scale their work. One possible explanation is that regulatory uncertainty contributes to senior talent leaving for countries with clearer AI policies. Select interview case studies reveal distinct localised talent strategies:

- **Acre Insights**
  bypasses the external market entirely, training local hires internally on specialised prompt engineering.
- **Myltura**
  hires affordable local junior developers and puts them through continuous, structured in-house training.
- **Danaya**
  builds junior technical capacity locally but had to recruit its CTO internationally, hiring a Cameroonian professional who'd built his entire career in France, since no equivalent candidate was available on the continent.

Responses to the question "WHERE DO YOU SOURCE YOUR AI TALENT"
(respondent n=122; multiple responses permitted)

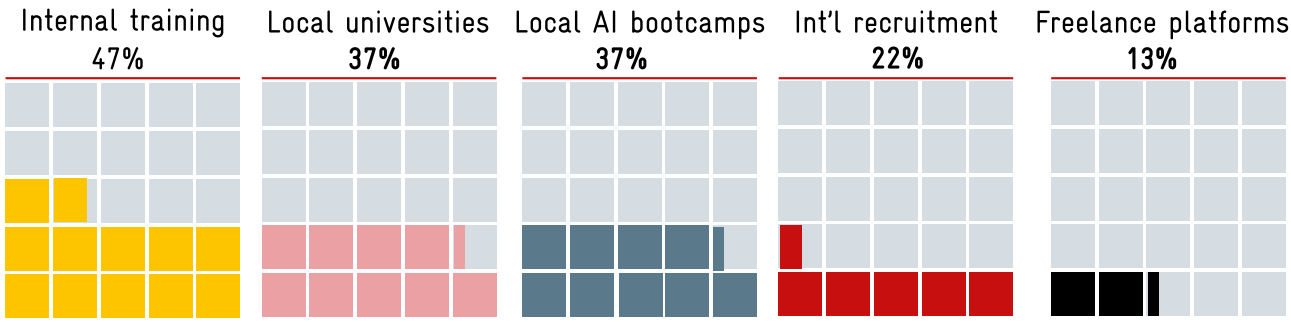


Figure 23: Proportion of surveyed responses by primary talent sourcing channels[38]

Source: African AI Business Survey (2026)

38. Note that respondents could choose multiple sourcing channels when answering this question in the African AI Business Survey (2026).

Because senior talent is globally scarce, companies become educational entities out of necessity. Businesses across Africa have built self-sustaining pipelines: 47% source talent through internal training, 37% leverage local AI bootcamps, and 37% recruit from local universities. While these businesses initially embraced internal training as an adaptive response to severe talent scarcity, the approach also produces important strategic benefits. In-house training enables companies to create expertise tailored to their own products, infrastructure, and organisational workflows in ways that external hiring often cannot. This effectively transforms workforce development from a short-term survival mechanism into a longer-term capability-building strategy.

A final crucial point here is that lack of talent availability and reliance on internal training are likely linked to the presence of third-party API models across operating ages and funding. While in-house and hybrid models require specialists, and even open source models require a degree of specialisation, third-party APIs let you "rent" another model, compressing the time it takes to hire or train people into becoming specialists.

Cloud and sovereign infrastructure challenges

The majority of AI development budgets are swallowed up by cloud computing, GPUs, and AI infrastructure (65% of companies), leaving data acquisition and R&D engineering significantly underfunded.

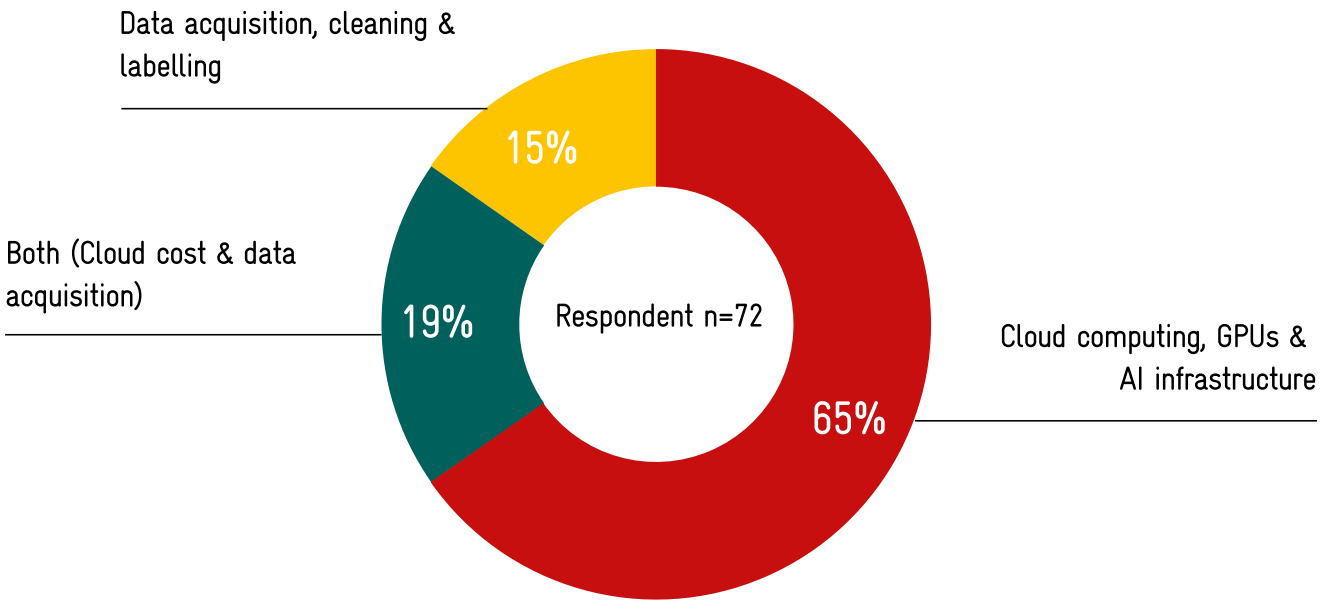


Figure 24: Proportion of surveyed businesses by top AI development budget spend[39]

Source: African AI Business Survey (2026)

Operating AI companies in regions with unstable national power grids means that building localised, capital-intensive private GPU clusters is functionally impossible for most. African companies are structurally dependent on global cloud providers, meaning that a massive portion of the financial upside of the African AI boom leaks back out of the continent in the form of foreign infrastructure expenditures.

39. Note that the chart reflects responses from 72 respondents. Responses including "Prefer not to disclose" and "Other" are not reflected in the chart.

Company Spotlight

MyItura

Using AI to reduce barriers to healthcare

HQ country: Nigeria

Years of Operation	Sector	Operational Country	AI Centrality
3	Health	Nigeria	AI-enabled

MyItura is a Nigerian health technology business founded to improve patient records across the country's fragmented healthcare system. The company started with a simple electronic medical records (EMR) platform, then expanded into telemedicine, laboratory test booking, and a "care now, pay later" service called MediLoan. AI became increasingly embedded across its products, including AI-enabled transcription of telehealth appointments to create standardised doctors' notes and patient records.

MyItura ended up building several products that address multiple issues along the value chain. First, they needed to create telemedicine platforms, then drive digital and AI adoption for doctors who may want to rely on traditional notetaking, and then create anonymised data infrastructure to enable treat-now-pay-later lending products. But developing all these products and scaling meant addressing infrastructural hurdles along the way.

First, MyItura found that much of the health data available to train earlier AI models was fragmented and unstructured local health data. So they built proprietary datasets to improve data quality. Scaling operations also meant they needed a lot more computing power. So MyItura built partnerships to access cloud computing credits to offset the high cost of training and deploying AI models. MyItura operates in communities where many primary healthcare facilities lack basic digital equipment needed to adopt AI-powered tools. Infrastructure and cloud cost challenges have prompted the company to secure grant funding to equip field agents with tablets that help healthcare centres digitise operations, and it is exploring Unstructured Supplementary Service Data (USSD) and Interactive Voice Response (IVR) technologies to deliver AI-enabled services in low-connectivity environments.

> "Developing AI products, testing them, and scaling them cost a lot on a monthly basis, and this can be a challenge for many companies operating in middle income countries."
>
> — **Shina Arogundade, Co-Founder and CEO**

Infrastructure is the biggest bottleneck for surveyed African AI businesses. Three key infrastructure gaps stand out: high cloud costs affect 61% of companies, limited GPU access (17%), and access to stable and robust internet connectivity (17%). Infrastructure gaps also spill into talent, with 15% of companies citing them as a reason they struggle to hire AI talent.

Most AI businesses rely on data that feeds their systems, which means they also need to access stable data storage through cloud storage or local data

centres. Data storage at a company level can quickly increase as a company scales and collects more data. Some companies have restrictions on storing their data in national data centres, which can further drive up cloud storage costs. Companies building machine learning or deep learning capabilities usually need access to several GPUs. Rising global demand has already pushed up their price, and that trend is expected to continue.[40] Unlike earlier SaaS companies, AI businesses need to factor in expensive costs of AI development at the core of their business model and growth pricing, and this means that early-stage companies without much funding or subsidised access to the infrastructure can face barriers to growth.

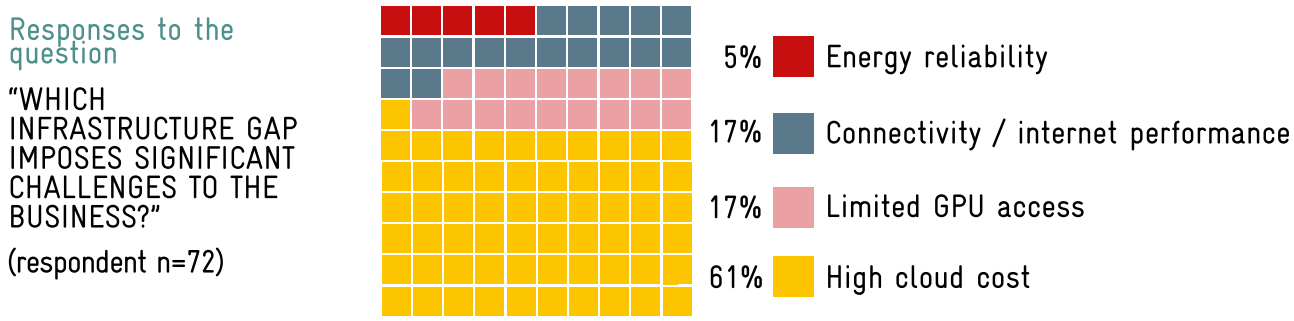


Figure 25: Proportion of surveyed businesses by primary infrastructure bottlenecks[41]

Source: African AI Business Survey (2026)

The energy reliability figure (5%) may understate the true significance of the constraint since most survey respondents are from Nigeria, Kenya, and South Africa, where generator backup and intermittent connectivity are common operating costs. The macroeconomic data exposes a regional challenge:

Sovereign infrastructure capacity

Africa accounts for less than 1% of global data centre capacity despite hosting 18% of the world's population.[42] Foreign servers (mostly in Europe) handle an estimated 80% of the continent's internet traffic[43]. South Africa, Kenya, and Nigeria together account for 41% of the continent's 223 data centres, meaning the remaining 35+ countries share fewer than 135 facilities.[44]

The energy paradox

The planned $1 billion geothermal-powered data centre in Kenya (Microsoft/G42) stalled by August 2025 because powering it would have required cutting supply to half the country[45]. In Nigeria, the national grid delivered an average available capacity of around 4,000 MW in early 2026 against a theoretical installed capacity of approximately 13,000 MW, which is a 31% utilisation rate.[46]

The currency trap

The Nigerian naira devaluation in 2023 led to a reported 224% increase in cloud service costs for some users when priced in local currency.[47]

40. Deloitte (2025)
41. Note that the chart reflects responses from 72 respondents. Responses such as "Don't know" are not reflected in the chart.
42. World Economic Forum (2025)
43. Agwaibor (2026)
44. African Energy Chamber (2025)
45. Butler (2026)
46. Premium Times (2026)
47. Wise Hustlers (2026)

The compute time gap

Only 5% of Africa's AI talent has access to the compute needed for complex tasks.[48] AI practitioners on the continent face waits of up to six days to iterate on models, compared to around 30 minutes for peers in G7 countries.

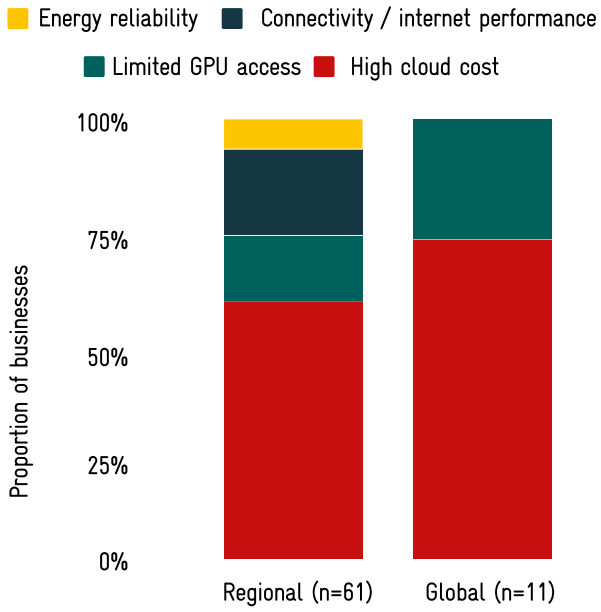


Figure 26: Proportion of surveyed businesses by infrastructure bottleneck & regional group[49]

Source: African AI Business Survey (2026)

Ultimately, infrastructure costs are a greater barrier for companies operational only in Africa compared to those operational beyond Africa. What makes this constraint particularly challenging for the businesses in this dataset is that AI businesses see infrastructure costs scale directly with usage. A traditional software or fintech company can scale its user base without a proportional rise in per-user compute cost, but AI businesses face these costs at global rates (typically USD) regardless of where the company operates or what its customers can pay. **This is why GPU access is so much harder to resolve through normal business growth alone: the more successful an AI-native company becomes, the more its infrastructure bill grows in lockstep, rather than flattening out the way it would for a conventional SaaS product.**

Companies operational only in Africa also cite connectivity/internet performance (17%) and energy reliability (5%), both of which are not mentioned by companies that operate beyond Africa. Taken together, the data suggest that companies operational only in Africa are more exposed to connectivity and energy constraints, and are more likely to be pre-profit and to use simpler architectures. These patterns may reflect infrastructure conditions, but they may also reflect differences in company age, funding or sector, which the study cannot separate.

Desired partnerships

A final bottleneck for surveyed AI businesses is regarding partnerships, where companies are highly active but resource-constrained. Most currently work with other startups (43%) and non-governmental organisations (NGOs), donors & development partners (40%), while government & public sector, plus large private sector companies are engaged by roughly a third of businesses.

48. UNDP (2024)
49. Note that these figures reflect responses to this specific question and therefore do not represent the full 85 survey respondents. Of those who provided a response, 13 reported operating both within and beyond Africa, while 66 reported operating exclusively within Africa. Any analysis of companies operating both within and beyond Africa should therefore be interpreted in the context of this lower response count. This chart reflects even fewer respondents due to some respondents not sharing their infrastructure bottlenecks.

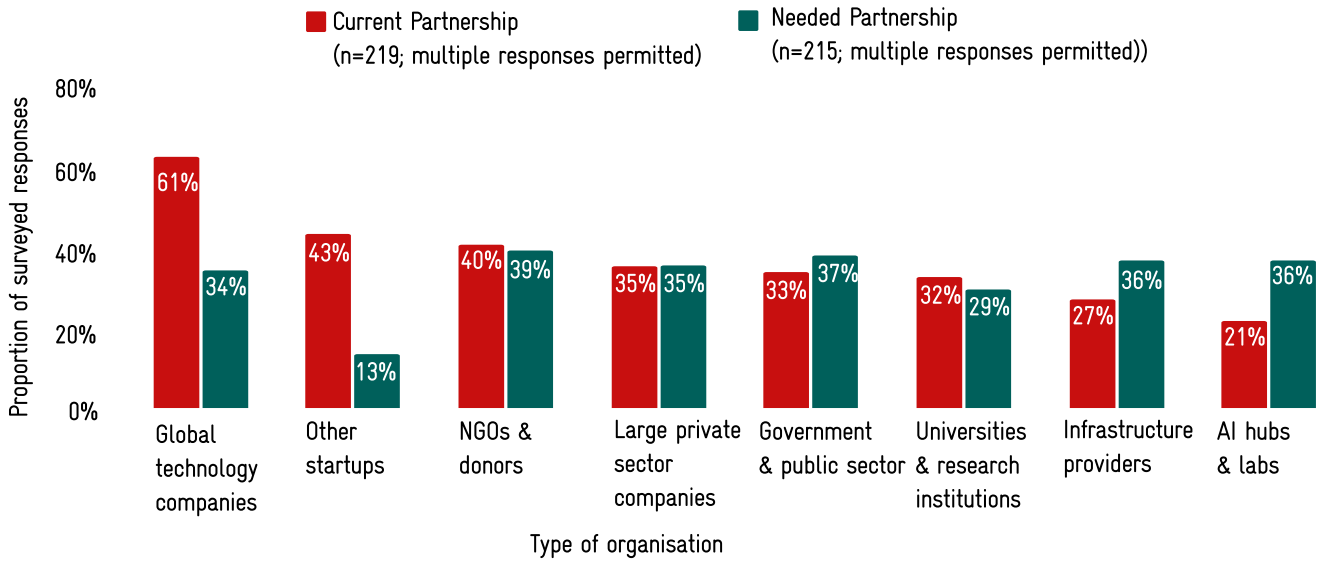


Figure 27: Proportion of surveyed responses by current & needed partnership types[50]

Source: African AI Business Survey (2026)

When looking to the future, the most-wanted partners are AI hubs or labs (36%), NGOs, donors & development partners (39%), infrastructure providers (36%), and government & public sector (37%). This distribution suggests that even well-networked African AI companies feel severely under-resourced on infrastructure access and require institutional backing to achieve long-term, sovereign scale.

> "Moving from short-term pilot projects to long-term institutional partnerships would significantly accelerate our growth and enable us to become the preferred...partner for organisations across Africa."

> "Partnership with government to provide AI solutions to all schools."

The prevalent demand for AI hubs and labs highlights a mismatch in the African support ecosystem. While the continent boasts over 470 generic innovation hubs, less than 5% possess the specialised technical mentorship, localised data repositories, or computational hardware required for AI development[51]. Some anonymised feedback from the survey reveals:

> "Public or private subsidies, AI governance, and digital sovereignty issues (are) all essential levers for structuring, securing, and accelerating business growth."

> "Access to strategic partners and ecosystems...through subsidised access or support programs."

To summarise the ecosystem bottlenecks founders shared: customer trust and literacy and cloud costs are the two dominant barriers, with infrastructure dependency cited as a top budget expenditure by two-thirds of surveyed AI businesses. Talent scarcity has pushed companies toward internal training as a default strategy, while founders want to see more specialised hubs to help address these infrastructure challenges. The next section turns to the role of the public sector, examining the policy interventions surveyed AI businesses see as most important for addressing these bottlenecks and creating a more enabling environment for growth.

50. Note that respondents could choose multiple partnerships when answering this question in the African AI Business Survey (2026).
51. AfriLabs (2022)

Section 6: Ecosystem needs for public-sector intervention

Key points

- AI-specific policies across the continent remain nascent, with founders often building products at a faster pace than the regulatory environment surrounding them.
- R&D/compute subsidies (62%) and cross-border data harmonisation (49%) top the list of policy interventions businesses want to see.
- A quarter of surveyed AI businesses want regulatory sandboxes, primarily for access to government data.

Many of the constraints facing surveyed African AI businesses extend beyond what companies can solve themselves. The cost of compute, fragmented access to data, and limited pathways for working with government datasets all point to a role for public-sector intervention. This section examines the policy priorities emerging from founders, including subsidies for R&D and compute, cross-border data harmonisation, government procurement, and regulatory sandboxes that could give businesses more room to experiment and scale.

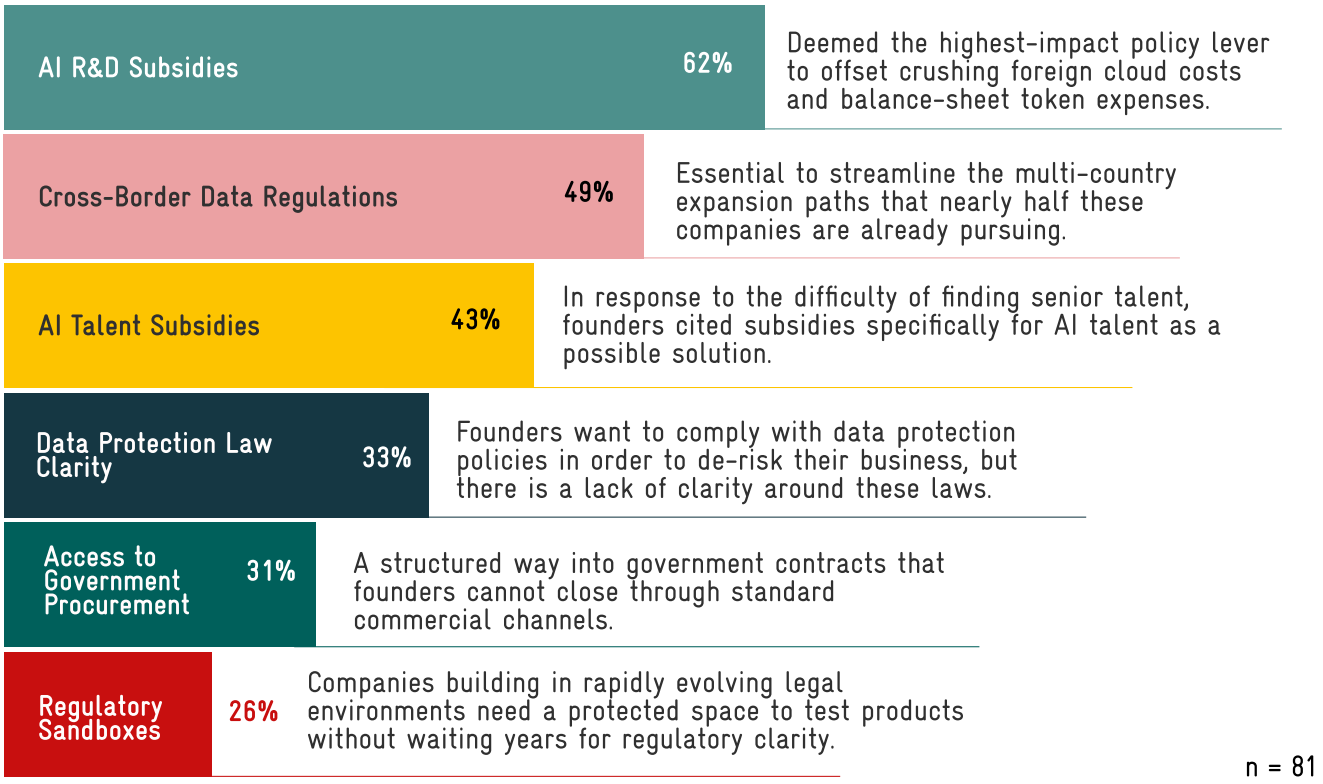


Figure 28: Proportion of surveyed responses by the most useful policy changes[52]

Source: African AI Business Survey (2026)

52. Note that respondents could choose multiple policies when answering this question in the African AI Business Survey (2026).

Subsidies

AI R&D subsidies are relevant to the entire value chain of AI tech development: data, human resources, cloud and compute costs, and commercial testing. Interviews reveal that businesses also see them as essential for funding the iterative research needed to improve AI systems. Given the previous sections mentioned financing, input costs (both cloud and data costs), and access to the right talent as barriers to scaling, R&D support at an early stage de-risks and helps companies bring out key products into the market. AI talent subsidies were mentioned as an important priority to develop and commercialise AI products on the continent, and since businesses are taking on much of the training on the job, subsidies should reflect the industry-led talent upskilling. For businesses developing proprietary models, the challenge is continuously collecting data, validating predictions, and refining models over time. Skilladder explains why many founders see R&D support as an investment in long-term innovation rather than short-term infrastructure alone.

Company Spotlight



Skilladder.ai

Why AI R&D subsidies matter beyond computing

HQ countries



Nigeria USA

Years of Operation	Sector	Operational Country	AI Centrality
1	Education	Nigeria	AI-native

Skilladder.ai is an AI-powered platform that measures and verifies workforce skills, giving employers, training providers, and recruiters a common language for readiness. It's building a standardised skills ontology that allows organisations to measure workforce readiness using a common language.

For Skilladder, building an AI product is only the first step. The main challenge is continuously improving the underlying models by extending and validating the skills ontology, running the psychometric work that keeps assessments reliable, and collecting high-quality workforce data at scale. The problem is solved through sustained investment in data collection, experimentation, model refinement, and computing infrastructure. For many early-stage companies, these research activities compete directly with the need to generate revenue and serve paying customers.

Banasko explains that AI R&D subsidies let companies fund that research instead of diverting limited resources toward immediate commercial delivery. That support gives companies room to build dedicated research capacity, strengthen the evidence behind their models, and develop AI systems better suited to African labour markets.

> "All cloud solutions require a subscription and end up costing a lot as you grow. Skilladder has found partners to help subsidise that cost as we grow and test our model. And as a young company, we need targeted advisory to understand how we can use our resources wisely."
>
> — **Kehinde Banasko, Founder and CEO**

Cross-border data and government procurement

49% of surveyed companies identify cross-border data regulations as a priority. Consulted data-governance practitioners noted that some African data-protection frameworks share common baseline principles, while differences in terminology, data classification and implementation can impede interoperability. The blocking point is not foundational disagreement between frameworks but divergent categorisation of specific data types, particularly around public interest data, security data, and definitions of data sovereignty, that prevents otherwise similar national frameworks from interoperating in practice. Kenya and Nigeria, for instance, define "sensitive data" differently in ways that directly affect whether cross-border data flows between the two countries are permissible.[53] As a result, founders want interoperability between regulations that are already fairly similar.

Finally, 32% of surveyed companies cite government procurement access as a priority. For the surveyed cohort which targets the government among their key customer base, and therefore faces long sales cycles, procurement access is the mechanism founders want for a customer relationship they're already pursuing. Qualitative interviews suggest founders want a mechanism for demonstrating value in a contained, lower-risk environment before a full contract is awarded.

Regulatory sandboxes

A quarter of surveyed AI businesses want regulatory sandboxes. Key reasons for joining a sandbox, according to respondents, were direct access to government data (34%), accelerated licensing or patents (21%), access to regulatory knowledge experts (18%) or a "no enforcement" grace period (18%).

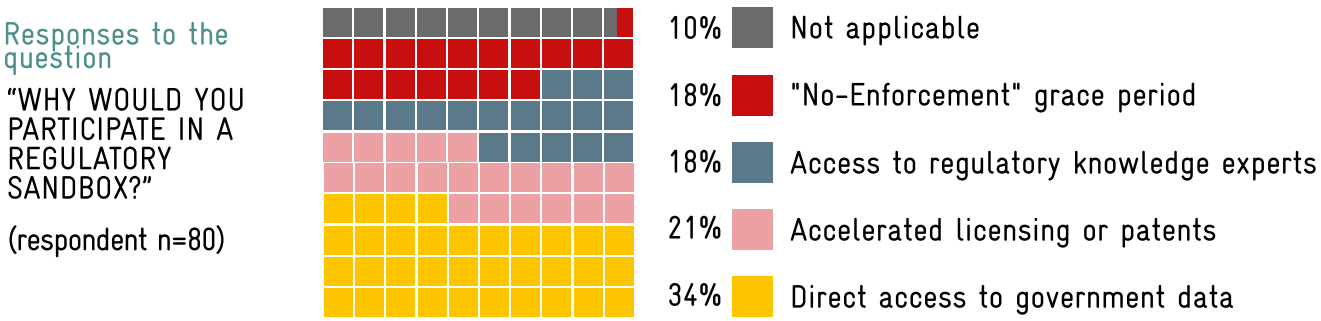


Figure 29: Proportion of surveyed businesses by how sandbox will help operations[54]

Source: African AI Business Survey (2026)

Further engagements with AI businesses revealed that they would benefit from understanding how a specific policy will impact their business. Companies would also like to access government-collected data in a sandbox environment to test how the data can be safely used by AI businesses.

Most AI businesses we spoke with indicated a desire to work with the government to help create a regulatory environment grounded in operational realities through their participation in a sandbox. The businesses named access to government data as a priority feature of a sandbox.

53. Interview with Patricia Boshe
54. Note that the chart reflects responses from 80 respondents. Responses including "I don't know" are not reflected in the chart.

Company Spotlight

Soil Solutions

Regulatory sandboxes to unlock public agricultural data

HQ country

Ghana

Years of Operation	Sector	Operational Country	AI Centrality
6	Agriculture & Agtech	Ghana	AI-native

Soil Solutions develops FarmAssist, an AI-powered precision agriculture platform that helps smallholder farmers improve productivity through localised agronomic advice. The company combines open source models with locally collected soil data, satellite imagery, Internet of Things (IoT) soil sensors, and decades of farming knowledge gathered through more than 350 field officers working directly with farming communities.

The company chose to localise existing AI models instead of building proprietary foundation models. Global models often lack the contextual understanding needed for African agriculture, making local data essential for producing useful recommendations. Some of the continent's most valuable agricultural datasets already exist within government institutions. Agricultural Extension Officers (AEOs) have accumulated decades of records on crops, soils, and farming practices, yet much of this information remains undigitised or inaccessible due to bureaucratic and regulatory barriers.

Samanhyia believes regulatory sandboxes could allow trusted companies to work alongside governments to digitise, test, and responsibly use public datasets while policymakers develop appropriate governance frameworks. For Soil Solutions, regulatory sandboxes are not simply about compliance. Rather, they are a pathway to unlocking public data for innovation while helping governments design AI policies grounded in practical implementation.

> "The data is there. What we need is a way to use it responsibly to improve productivity."
>
> — **Moses Samanhyia, Founder**

Across these policy priorities, a consistent message emerges: surveyed African AI businesses are asking for practical conditions that enable local companies to build, test and scale responsibly. R&D and compute subsidies can reduce the cost of developing AI, interoperable data rules can make cross-border expansion easier, and regulatory sandboxes can create practical pathways for businesses to work with public data and institutions. Taken together, these interventions point to a broader role for the public sector: not just setting the rules for AI, but helping build the infrastructure, data access, and market conditions that allow an African AI ecosystem to develop on its own terms. The conclusion brings these findings together and considers what they mean for the next phase of African AI.

Conclusion

The findings indicate that many surveyed African AI businesses are doing more than adopting a global technology trend. They are adapting commercial and technical models to the realities of the markets in which they operate. The mapped and surveyed datasets, read together, tell a consistent story: an ecosystem that is young but not new, concentrated in a handful of tech hubs, and shifting decisively from AI-adoption toward AI-creation as newer cohorts build AI-native from day one.

With this ecosystem shift, the ecosystem around these businesses, including capital, infrastructure, talent pipelines, and regulatory environment need to adapt at the same pace. Surveyed African AI businesses build and sell into a market shaped by institutional buyers with long sales cycles, price sensitivity that reflects local purchasing power rather than product quality, and a cost base priced at global rates regardless of where revenue is earned. This asymmetry runs through nearly every finding in this report, and closing it is not something any single actor can do alone.

Surveyed businesses identified the following priorities for different ecosystem actors:

Founders

Businesses express a continued focus on sharing perspectives through ongoing research, ecosystem representation, and active engagement with hubs to help investors, policymakers, and consumers better understand the opportunities and challenges in scaling local AI solutions.

Hubs and ecosystem support organisations

The surveyed AI businesses require specialised technical and operational support rather than generic incubation and investment readiness. Hubs should serve as centralised access points for localised datasets, talent pipelines, infrastructure credits, and domain-specific mentorship, while facilitating industry representation and knowledge sharing across emerging business models.

Investors

The surveyed AI businesses across Africa are delivering localised solutions despite structural constraints by diversifying revenue streams and serving multiple customer segments. Investors can support this momentum by actively participating in ecosystem dialogues, engaging with local hubs and academic institutions to identify early-stage opportunities, and co-developing commercial pathways for emerging AI applications.

Policymakers

Given this landscape is changing quickly, policymakers should learn and co-design with local businesses and industry experts to identify responsive policies suitable for each country.

We welcome the opportunity to continue this conversation with all stakeholders. Whether you are an AI business founder, investor, ecosystem builder, policymaker, we invite you to investigate these findings further together. To share your insights or explore partnerships for the next phase of this work, please reach out to us directly at saba.tiku@giz.de.

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Annex

A. List of AI business interviewees

Interviewee name	Organisation or Affiliation	Interview date
Catherine Njeri	Acre Insights	11 May 2026
Shina Arogundade	MyItura	11 May 2026
Gauthier de Gerlache	Danaya	12 May 2026
Abdoulaye Faye	Galsen AI	15 May 2026
Priaash Ramadeen	The Awareness Company	19 May 2026
Kehinde Banasko	Skilladder	6 June 2026
Aibaki Tembo	MPhando	8 June 2026
Regan Muthoni	Cosmobits	9 June 2026
Esther Olalude	Venille	9 June 2026
Moses Samanhyia	Soil Solutions	16 June 2026
Stacy Obiero	Ignitia	22 June 2026
Patricia Boshe	Africa Digital Rights Hub	9 July 2026

B. List of other stakeholder interviewees

Interviewee name	Organisation or Affiliation	Interview date
Yomna Omran, Suzanne El Akabaoui	Egypt's Personal Data Protection Center (PDPC)	13 July 2026
Claude K. Migisha	AI and Data Governance Consultant, Research ICT Africa	20 July 2026

C. List of virtual validation session participants

Interviewee name	Organisation or Affiliation	Validation session date
Suzanne El Akabaoui	Egypt's Personal Data Protection Center (PDPC)	15 July 2026
Hemansu Keeka	Disraptor	15 July 2026

Patricia Boshe	Africa Digital Rights Hub	15 July 2026
Maxwell Ababio	Ghana Data Protection Commission	15 July 2026

D. Abbreviations

AEOs	Agricultural Extension Officers
AI	Artificial Intelligence
AML/CFT	Anti-Money Laundering and Countering the Financing of Terrorism
API	Application Programming Interface
AU	African Union
AUDA-NEPAD	African Union Development Agency – New Partnership for Africa's Development
AWS	Amazon Web Services
B2B	Business-to-Business
B2B2C	Business-to-Business-to-Consumer
B2C	Business-to-Consumer
B2G	Business-to-Government
BMZ	German Federal Ministry for Economic Cooperation and Development
CEO	Chief Executive Officer
CPU	Central Processing Unit
CTO	Chief Technology Officer
EMR	Electronic Medical Records
G7	Group of Seven (Canada, France, Germany, Italy, Japan, the UK and the US)
GenAI	Generative Artificial Intelligence
GIS	Geographic Information System
GIZ	Deutsche Gesellschaft für Internationale Zusammenarbeit
GPU	Graphics Processing Unit
HQ	Headquarters

HR	Human Resources
ICT	Information and Communication Technology
ID	Identification
IoT	Internet of Things
IVR	Interactive Voice Response
KYB	Know Your Business
KYC	Know Your Customer
LLM	Large Language Model
MLOps	Machine Learning Operations
MSME	Micro, Small and Medium Enterprise
MW	Megawatt
NGO	Non-Governmental Organisation
NLP	Natural Language Processing
OCR	Optical Character Recognition
PDPC	Personal Data Protection Center (Egypt)
PE	Private Equity
PEP	Politically Exposed Person
R&D	Research and Development
SaaS	Software-as-a-Service
SMS	Short Message Service
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
USD	United States Dollar
USSD	Unstructured Supplementary Service Data
VC	Venture Capital

E. Additional mapped AI business analysis

AI businesses are present across all regions, though activity is unevenly distributed. Most activity is concentrated in Eastern, Western, and Northern Africa, with Kenya, Nigeria, and South Africa leading. Central Africa remains a nascent ecosystem, with only a few emerging innovations.

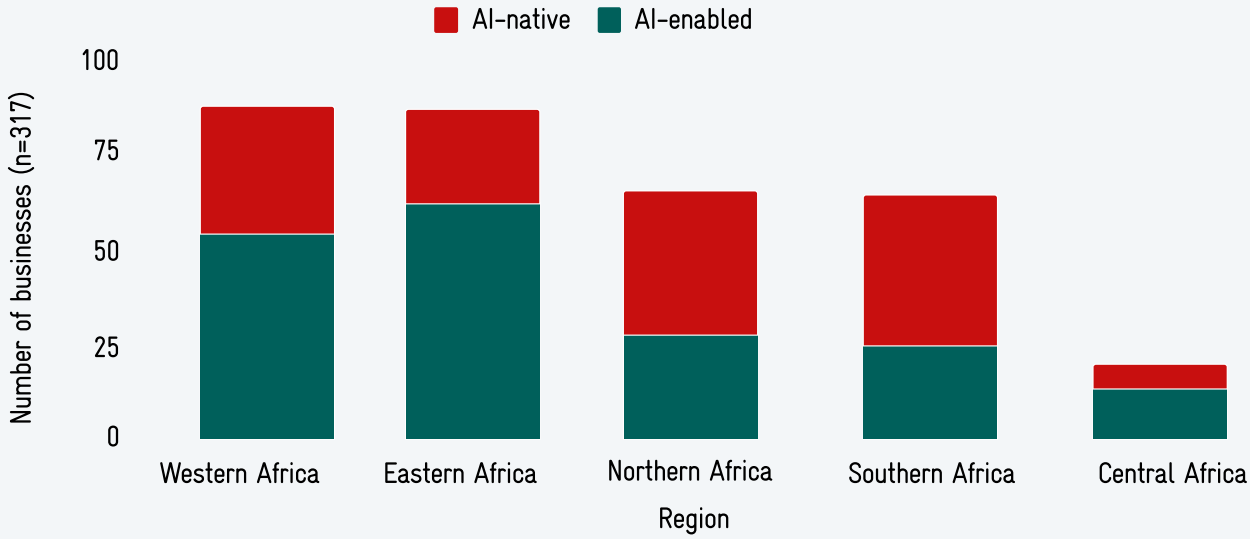


Figure 30: Number of mapped businesses by region and centrality[55]

Source: Briter Intelligence (2026)

The mapped companies operated across a range of sectors. This reflects how artificial intelligence is being applied in different industries, from digital services to sectors such as agriculture and healthcare. Software-as-a-Service (SaaS) was the most prevalent type of mapped AI business, which provides specialised AI solutions that can be applied across multiple sectors. The AI SaaS differs from the traditional SaaS model where the solution reduces human interactions for analysis by introducing end-to-end autonomous functionalities. AI SaaS as a sector will likely need to be differentiated from traditional SaaS in that they tend to work more end-to-end from data architecture to automated analysis and decision support and differentiated pricing model that relies more on pay-per-use rather than subscription, but for the interest of this report, SaaS will be used to describe the AI products that perform AI solutions across sectors.

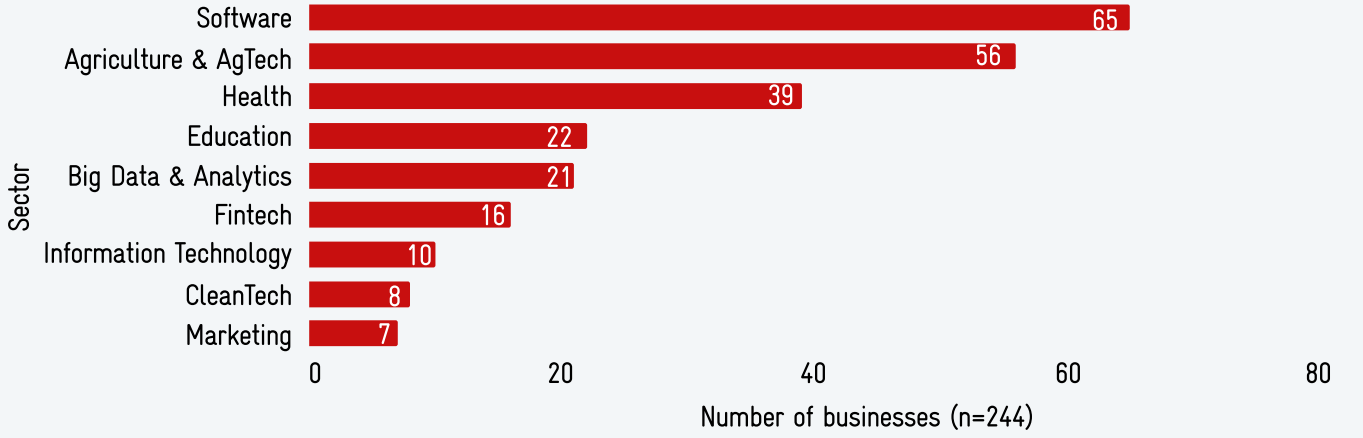


Figure 31: Number of mapped businesses by top sectors[56]

Source: Briter Intelligence (2026)

55. Some mapped AI businesses have more than one operating region, and therefore the sample size in this analysis is 317, which is larger than the 311 total mapped AI businesses.
56. The number of mapped AI businesses that operate in the top sectors shown in the analysis are 244. The total number of mapped AI businesses is 311.

In the mapping, more than half of the AI businesses were AI-enabled businesses, meaning they are more adopters of the technology rather than developers of new artificial intelligence products. However, when looking at the breakdown by their founding years, newer mapped AI businesses are AI-native, instituting AI solutions at the core, signaling a shift from use to creation.

The African AI business ecosystem is relatively still young. Across AU regions, most mapped AI businesses are in the growth stage (3-7 years old), 28% early-stage (0-2 years old), and only 23% over 7 years old. This young yet growing ecosystem reflects the recent growth of AI technologies at enterprise levels. Amongst AU regions, North and Southern Africa show relatively more long-established businesses, with South Africa and Kenya leading this trend.

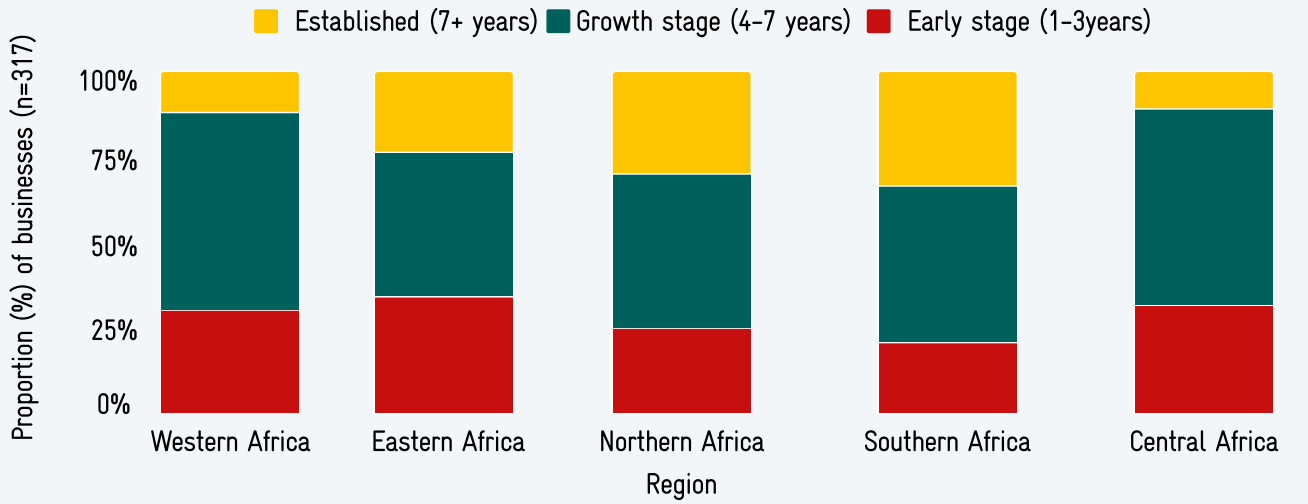


Figure 32: Proportion of mapped businesses by AU regions and age[57] Source: Briter Intelligence (2026)

Mapped AI businesses in the pre-AI era (before 2020) account for over 75% of the total funding across all ticket sizes and have raised larger ticket sizes. The newer cohorts of companies like GenAI Cohort (2023+) or Transition companies (2021-2022) are still more concentrated in the smaller ticket size, although some larger raisers show up. In the broader ecosystem across Africa, businesses take 2 to 3 years to fundraise their first round, and many of the new mapped AI businesses have not fundraised yet.

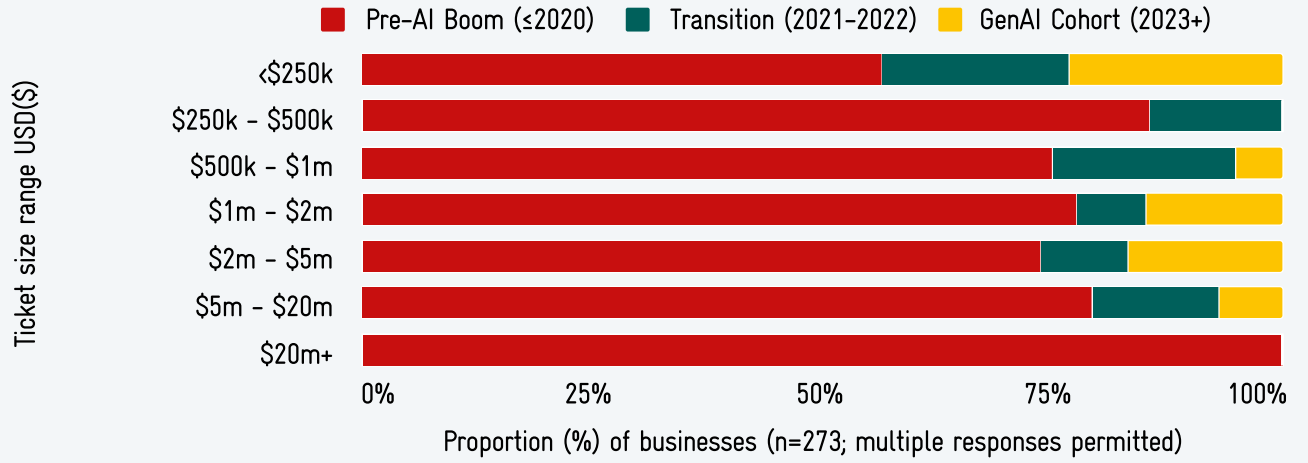


Figure 33: Proportion of mapped businesses by cohort group and ticket size[58] Source: Briter Intelligence (2026)

57. Some mapped AI businesses have more than one operating region, and therefore the sample size in this analysis is 317, which is larger than the 311 total mapped AI businesses.
58. The sample size of 273 are mapped AI businesses that have fundraised with disclosed funding ticket sizes. Some mapped AI businesses have fundraised multiple times, which is reflected in the overall sample size. Mapped AI businesses that are bootstrapped (i.e., have never fundraised), or have fundraised but have not disclosed fundraising records, or those that disclosed fundraising records without ticket sizes are excluded from this analysis.

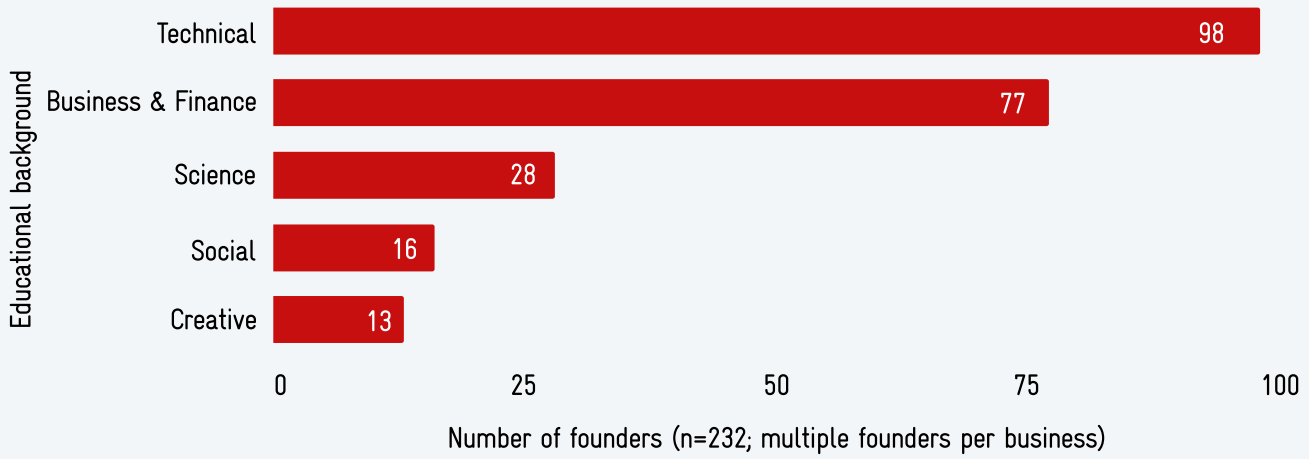


Figure 34: Educational background of mapped AI business founders[59] Source: Briter Intelligence (2026)

Most mapped AI businesses operate in English-speaking environments, reflecting the concentration of AI activity in those markets. A smaller share operates in Arabic- and French-speaking contexts, while only a very small number are based in Portuguese-speaking environments. But this scale difference is proportional to the relatively small number of Portuguese speaking markets (Mozambique being a major market) within Africa, compared to Anglophone or Arab-Franco speaking countries.

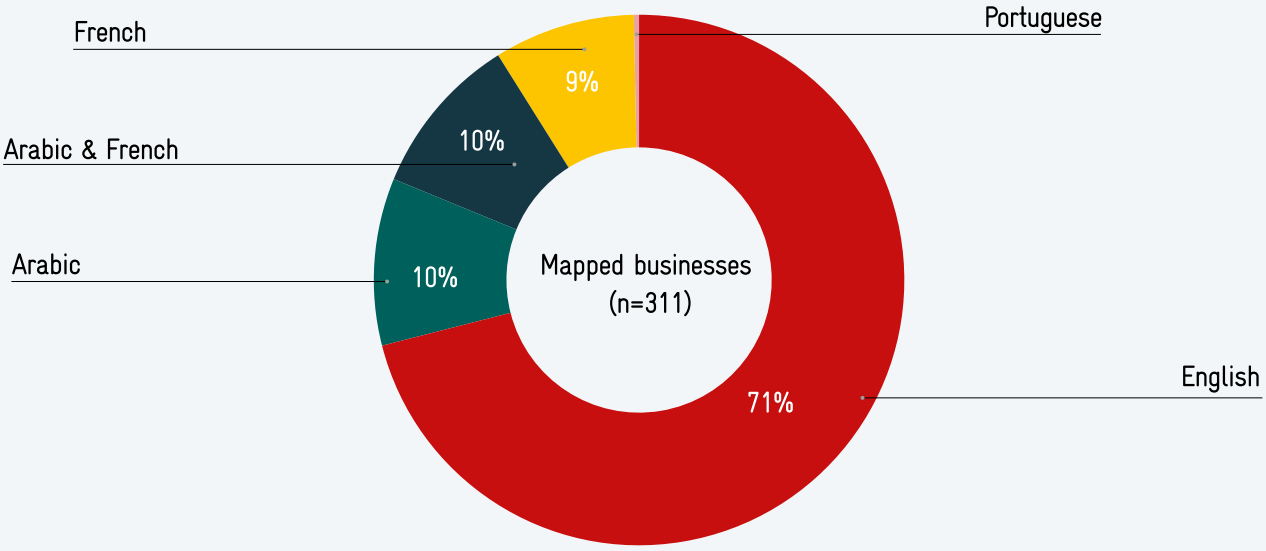


Figure 35: Language distribution of mapped businesses Source: Briter Intelligence (2026)

59. The sample size of 232 are mapped AI businesses with at least one known founder. Many mapped AI businesses have more than one founder, which is reflected in the overall sample size. Mapped AI businesses without disclosed founder information are excluded from this analysis.

F. Additional surveyed AI business analysis: AI source

At the early stage, companies split relatively evenly across in-house, open source, third-party APIs, and hybrid approaches. This distribution reflects founders testing different architectures based on what is most accessible at launch. Early-stage companies with technical founders might build in-house from day one, while those focused on speed-to-market rely on third-party APIs, and resource-constrained teams default to open source.

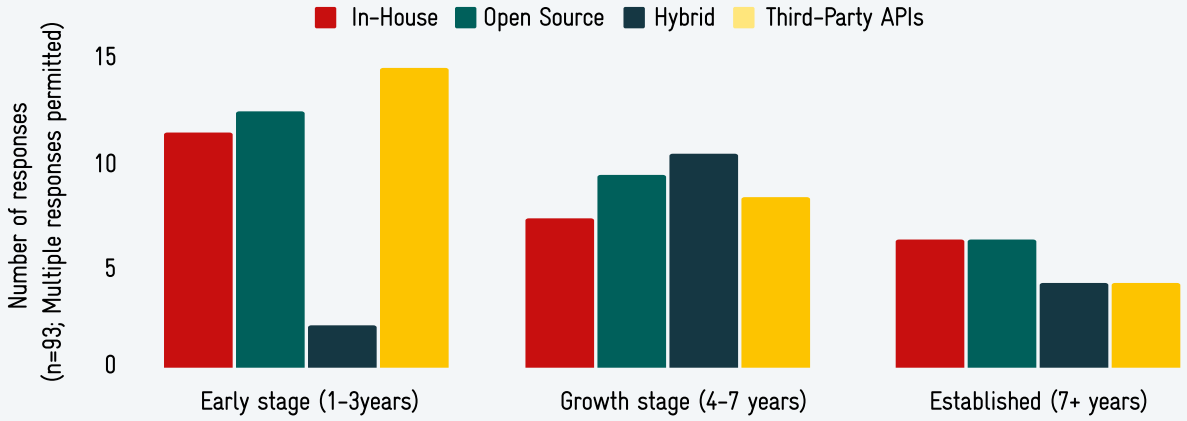


Figure 36: Number of surveyed responses by operational age and AI source[60]

Source: African AI Business Survey (2026)

As companies reach the growth stage, the distribution begins to shift. Hybrid approaches become more prevalent, nearly matching open source. This shift suggests companies are starting to layer proprietary capabilities on top of open foundations. At the established stage (7+ years old), the absolute dominance of any single strategy disappears as companies use a mixture of solutions that work across their AI products and services.

This shift is likely a strategic choice to match their specialisation needs and cost. For example, Cosmobits, a Kenyan AI credit scoring service, shared that while open source eliminates licensing fees, reduces per-query costs, and provides flexibility, open source also requires more time to tweak and customise, especially for analysing larger datasets. Similarly, Skilladder, a Nigerian HR Tech AI business, uses a mixture of in-house and open source models (hybrid model) to build skill scoring and anti-cheating measures. They pointed out that contextualisation is key to their AI product accuracy as they collect data from training organisations and employers that work with tech talents, and need to build domain knowledge that contextualises the data for meaningful analysis.

Research supports this pattern globally. The Linux Foundation's 2025 Economic and Workforce Impacts of Open Source AI report found that 89% of AI-equipped organisations use open source, but typically as a foundation layer rather than the entire stack.[61] This mirrors a global trend: open source remains critical, but becomes one component of a larger, differentiated system rather than the primary value proposition.

60. Note that respondents could choose multiple responses when answering this question in the African AI Business Survey (2026).
61. Linux Foundation (2025)

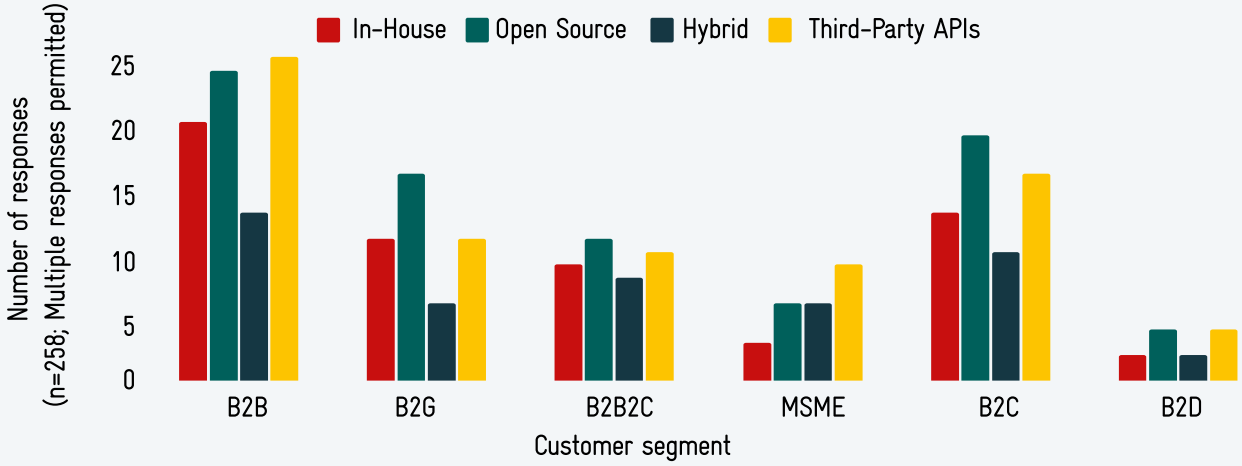


Figure 37: Number of surveyed responses by customer segment and AI source[62]

Source: African AI Business Survey (2026)

Hybrid architectures, which may offer more favourable long-run economics for companies that can afford the upfront investment, are the least common across nearly all customer segments, while third-party APIs remain prevalent. One possible explanation is that hybrid setups require significant upfront investment before they deliver value[63]. For early-stage companies operating with <$500K in funding (30% of the dataset), this upfront investment is prohibitive. Third-party APIs, by contrast, can be integrated in days or weeks with minimal infrastructure. A developer can call OpenAI's API, Claude's API, or Google's Gemini API directly from application code without building any AI infrastructure. Nevertheless, this report does not compare costs by architecture, so the relative economics cannot be confirmed.

For companies in the pilot or pre-revenue stage (40% of the dataset), time-to-market matters more than long-term cost optimisation. Spending half that time building hybrid infrastructure delays revenue generation and increases the risk of running out of capital before proving traction. Third-party APIs enable faster iteration, customer testing, and revenue generation, even if the unit economics are worse in the long term.

Another surprising finding is the prevalence of third-party APIs in B2G segments (10 companies) given data sovereignty concerns. Public-sector buyers may be expected to favour solutions where data stays within national or regional boundaries and algorithms can be audited for bias and accuracy. This would seemingly favour open source (18 companies) or in-house (12 companies) over third-party APIs that route data through foreign servers. However, many government agencies lack the internal technical capacity to evaluate complex AI infrastructure. A solution that works via API is easier to pilot and procure than one requiring extensive integration with legacy government systems. Additionally, many African countries lack clear AI governance frameworks. In the absence of explicit data localisation requirements, companies default to whatever architecture works fastest. One possible implication is that, as data localisation rules mature, some B2G providers may shift toward hybrid or in-house solutions. Finally, it's worth noting here that companies reporting "third-party APIs" as their primary source may still use open source or in-house models for sensitive components. A KYC verification platform might use third-party APIs for generic natural language processing (NLP) tasks (entity extraction, language detection) while

62. Note that respondents could choose multiple responses when answering this question in the African AI Business Survey (2026).
63. A company pursuing a hybrid strategy needs to: (1) set up compute infrastructure (cloud instances or local GPU clusters), (2) build MLOps pipelines for model versioning, training, and deployment, (3) hire specialised talent (MLOps engineers, infrastructure specialists), (4) acquire and clean training data for fine-tuning, and (5) develop monitoring and evaluation systems to track model performance over time.

running facial recognition or document verification on in-house infrastructure. The survey classification captures the dominant pattern, not the full architectural reality.

G. Additional surveyed AI business analysis: AI tech stack

When we examine model source by tech stack, a striking exception emerges:

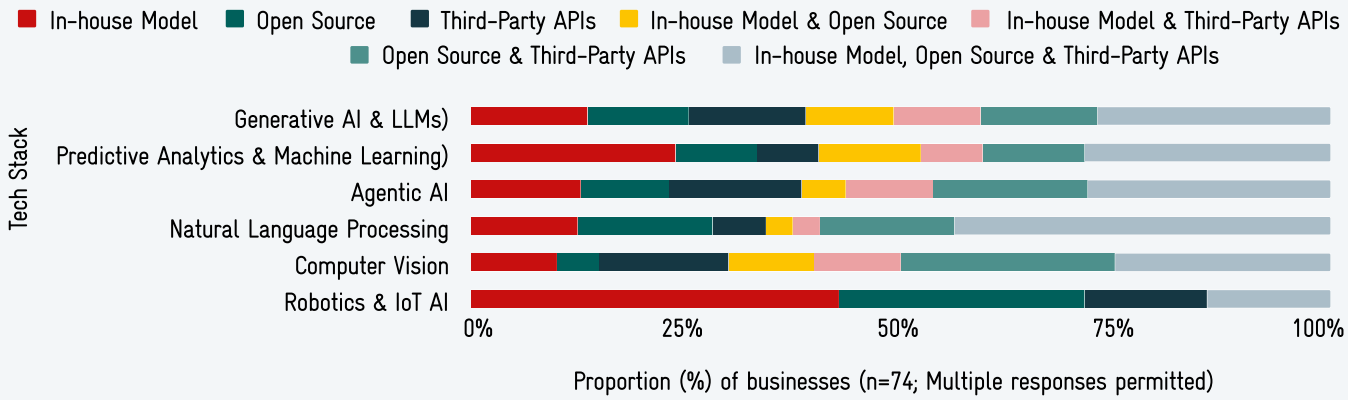


Figure 38: Proportion of surveyed AI businesses by tech stack and AI source[64]

Source: African AI Business Survey (2026)

In contrast, GenAI & LLMs show the most balanced distribution across all sourcing strategies. This reflects the maturity and diversity of the LLM ecosystem. The "hybrid" approach is particularly prevalent among GenAI companies as founders use open source foundation models as a cost-effective base and build proprietary fine-tuning, retrieval systems, and application logic on top. This architecture preserves cost efficiency at the foundation layer while enabling proprietary development where it creates competitive advantage.

H. Additional surveyed AI business analysis: bottlenecks to talent acquisition and retention by AU regions

Bottlenecks appear broadly similar across regions. Northern Africa shows a somewhat higher share of talent loss to international or remote roles, which may reflect the availability of Arabic-speaking roles in the Middle East or French-speaking roles in Europe. However, regional sample sizes of surveyed AI businesses are too small to draw firm conclusions.

64. Note that respondents could choose multiple tech stacks when answering this question in the African AI Business Survey (2026).

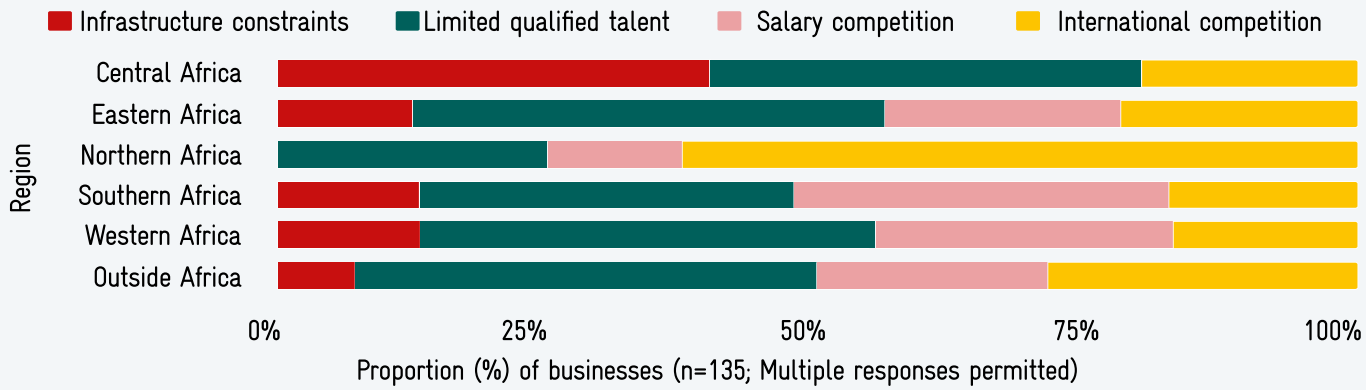
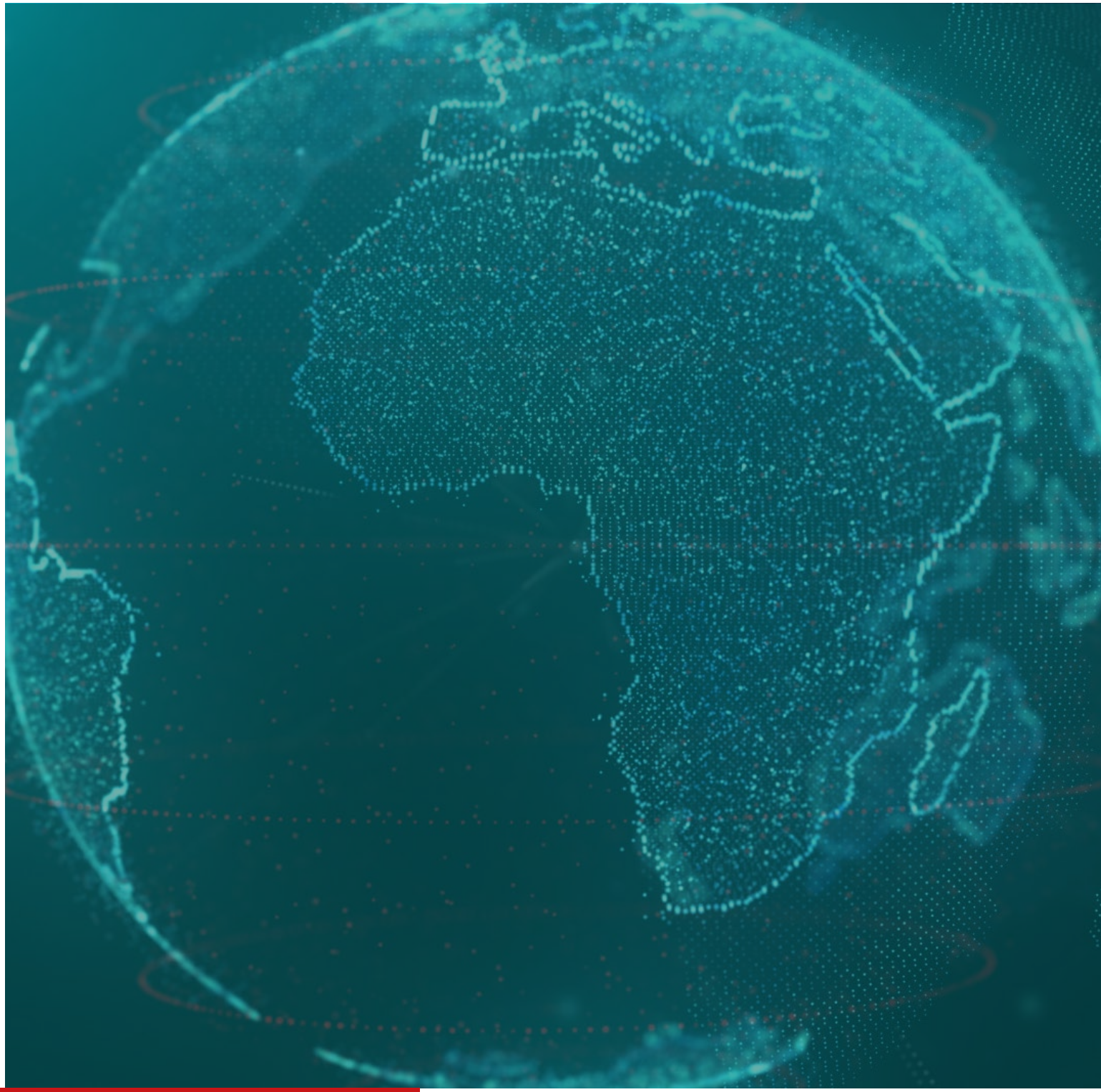


Figure 39: Proportion of surveyed AI businesses by AU regions and primary AI talent challenges[65]

Source: African AI Business Survey (2026)

65. Note that respondents could choose multiple primary AI talent challenges when answering this question in the African AI Business Survey (2026).



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