

AI and Evaluation: Exploring Made in Africa Approaches for Transformational Practice

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Background: Transformation-focused evaluation calls for evaluation to embrace complexity, systems thinking, and decolonial approaches in response to interconnected global crises. Artificial intelligence (AI) is increasingly used in evaluation practice, but its deployment raises critical questions about power, epistemology, and justice that remain underexamined, particularly in relation to transformational evaluation values.

Purpose: To examine how AI may both support and hinder evaluation's transformational imperative, using the African continent as a case example. The article explores the intersection of Made in Africa Evaluation (MAE) and Made in Africa AI (MAAI) as complementary movements, asking how AI can be adopted within evaluation practice without reproducing colonial patterns of extraction and dominance, and what infrastructures and competencies evaluators need to integrate AI responsibly within transformational agendas.

Setting: The African continent, with comparative perspectives from Canada and the United States.

Intervention: Not applicable.

Research Design: A qualitative landscape study combining semi-structured interviews with secondary analysis of institutional reports, academic literature, and policy documents.

Data Collection and Analysis: Semi-structured interviews conducted with MERL practitioners, AI Africa specialists, and sector experts across seven African countries (South Africa, Egypt, Nigeria, Kenya, Zimbabwe, Burkina Faso, and Uganda), plus Canada and the United States, complemented by systematic review of institutional reports, academic literature, and policy documents.

Findings: African evaluators' use of AI for MERL remains in early, exploratory stages, constrained by tool unsuitability, language and data infrastructure gaps, weak policy frameworks, and extractive data practices. Aligning AI with MAE principles—African agency and ownership, epistemological pluralism, participatory design, contextual grounding, and a transformation-focused orientation—offers a pathway toward AI that supports rather than undermines transformational evaluation, but this requires evaluators to actively shape AI development to align with our values and principles, creating space for those who resist AI applications that contradict these foundations.

Keywords: *made in Africa AI; decolonized AI in evaluation; AI in Africa evaluation.*

Other articles in this compendium have explored various dimensions of transformation-focused evaluation, an approach that supports deep, systemic changes in how evaluation is practiced to foster transformational learning and change (Chaplowe & Hejnowicz, 2021). Transformation-focused evaluation responds to urgent global challenges by moving beyond conventional evaluation practices to embrace complexity, systems thinking, and decolonial approaches (EvalSDGs, 2023). The transformational imperative refers to the urgent need for evaluation to fundamentally shift its methods, values, and power structures to address interconnected global crises—including climate breakdown, inequality, and epistemic injustice—that threaten planetary and human wellbeing (Chaplowe & Mukoma, 2023).

Building upon these foundations, this article examines how artificial intelligence (AI) and AI systems may both support and hinder this transformational imperative, with particular focus on the African continent as a case example of how these dynamics manifest in practice. While technological and data science advances stem from intersecting forces—including commercial interests, scientific innovation, policy frameworks, and development sector demands—their deployment in evaluation contexts raises critical questions about power, epistemology, and justice (Birhane, 2023).

The central questions guiding this inquiry are:

- How can AI technologies be adopted within evaluation practice without reproducing colonial patterns of extraction and dominance?
- What essential infrastructures and competencies do evaluators need to integrate AI systems responsibly within transformational agendas?

To address these questions, we examine the intersections between Made in Africa evaluation (MAE) and Made in Africa AI (MAAI) as complementary movements. Together, they illuminate pathways toward AI adoption that centers African epistemologies while promoting equitable and sustainable evaluation practice.

This article first examines the promises driving AI adoption in evaluation, including evidence of current usage patterns. We then analyze fundamental tensions between current AI systems and transformational values through environmental, labor, and epistemic dimensions. After situating these dynamics within the broader context of polycrisis and AI evolution, we explore how MAE and MAAI movements offer practical guidance for responsible AI integration in

evaluation practice. Given the pace of AI development, claims about “current” capabilities require careful dating and periodic reassessment.

The Appeal of AI for Evaluation Practice

Many evaluators are excited by AI’s potential to transform how evaluation is done. Advanced AI systems, particularly large language models (LLMs) and machine learning applications, promise to expand human analytical capacity by identifying patterns in massive data sets that would be impossible to detect manually (Humeau & Deshpande, 2024). Proponents suggest AI could reduce data processing costs, enabling evaluators to invest more time in relationship-building and interpretive work that only humans can perform (Nielsen et al., 2025). Within resource-constrained social sector organizations, AI efficiencies could potentially reduce evaluation costs while freeing funding for core mission activities.

Beyond efficiency gains, some argue AI could support decision-making in a polycrisis—the convergence of overlapping emergencies including climate change, biodiversity collapse, economic inequality, and political instability (Lawrence et al., 2024). Advocates propose that AI could widen the scope of evidence used, increase the speed of feedback loops, and support adaptive management at scale. Specific claims about AI’s transformational potential include enhanced natural language processing of qualitative data (Leeson et al., 2019), automated coding and thematic analysis, and predictive analytics for development outcomes. However, evidence showing that these promised capabilities translate into improved evaluation quality, equity, or impact remains limited and contested (Head et al., 2023).

At a practical level, people around the world, including evaluators, are already using AI in their daily work. The Center for Effective Philanthropy found that two-thirds of foundations and nonprofits surveyed in 2025 were using AI, primarily for internal productivity and communications, with almost all showing interest in increasing their use (Arrillaga et al., 2025). Research on ChatGPT adoption shows disproportionately high uptake in many low- to middle-income countries, with most usage focused on practical guidance, information seeking, and writing tasks, particularly editing and translation rather than generating text from scratch (Chatterji et al., 2025).

Alongside enthusiasm, organizational leaders acknowledge concerns about security, accuracy, staff expertise, bias, and trade-offs between

efficiency and authenticity (Arrillaga et al., 2025). These practical adoption patterns demonstrate that AI has moved from theoretical possibility to everyday reality across the evaluation ecosystem. However, to understand whether these applications can align with transformational imperatives, we must examine the material, economic, and epistemic foundations of current AI systems.

Fundamental Tensions Between AI Systems and Transformational Values

As AI adoption expands across the evaluation ecosystem, deeper questions arise about alignment between the design and deployment of commercial AI systems and the values that underpin the transformational imperative. The transformational imperative emphasizes questioning power structures, adopting decolonial approaches, working to end inequality and epistemic injustices, and addressing climate and other interrelated global crises. Raftree (2023) shows how dominant AI paradigms conflict with evaluation commitments to equity, justice, participation, environmental sustainability, and epistemic pluralism.

For evaluators, these tensions are not abstract. They shape what is counted as value, whose knowledge is recognized, and which outcomes are prioritized.

Environmental and Material Harms

Perhaps the most visible contradiction lies in AI's environmental footprint. Training LLMs and operating supporting data centers require vast amounts of energy and water, contributing to climate change and resource depletion (MIT Technology Review, 2025). This creates a practical paradox: AI is often promoted as a tool for climate mitigation (Climate Change AI, n.d.), yet its infrastructure intensifies the very environmental pressures transformation-focused evaluation seeks to address.

The scale is significant. A single Amazon data center complex in Indiana is projected to draw 2.2 gigawatts of electricity and up to 2.2 million gallons of water per hour (Weise & Metz, 2025). Across the United States, data centers used an estimated 17 billion gallons of water for cooling in 2023, with sharp increases expected (McCauley & Scanlan, 2025).

Although Africa currently represents only about 2.5% of the global AI market (Microsoft, 2025), the continent may face disproportionate

environmental strains as AI adoption grows, particularly in settings marked by water scarcity, fragile energy systems, and limited regulation. For evaluators working in contexts shaped by overlapping ecological and social crises, these environmental costs raise fundamental questions about what is included or excluded when program value is assessed.

Labor Conditions and Economic Dynamics

Environmental impacts are closely tied to the labor arrangements that make AI systems possible. In Kenya, data labelers have reportedly earned as little as US\$1.32–2.00 per hour for content moderation and data annotation (Perrigo, 2023). As Chinagorom-Abiakalam (2025) notes, African data workers remain largely invisible; behind the smooth interfaces of chatbots lies labor that is underpaid, repetitive, and emotionally demanding.

This landscape defies binary accounts. AI is projected to create up to 230 million jobs across Africa by 2030 and add up to US\$2.9 trillion to the continent's GDP (African Union Development Agency-NEPAD, 2024; Brookings Institution, 2024). Yet precarity persists, particularly in countries like Kenya where youth unemployment remains at 67% (International Labour Organization, 2023).

The labor chains underpinning AI have been widely described as extractive and marked by low pay, insecure employment, and routine exposure to harmful content (Data Workers Inquiry, 2025; Gray & Suri, 2019). The data fueling these systems has often been taken from platforms and creative works without consent or compensation (Okorie & Marivate, 2024). Scholars describe these patterns as digital colonialism: Infrastructure, capital, and profits concentrate in the Global North while data, labor, and risk shift to the Global South (Chinagorom-Abiakalam, 2025). Africa contributes less than 1% of global internet content, and despite 223 data centers across 38 countries, much infrastructure remains tied to external providers (Banya, 2025). Proximity to infrastructure does not guarantee control or sovereignty (Gothoskar, 2024).

For evaluators, these dynamics complicate claims about AI-driven efficiency, innovation, and development impact. They raise questions about whose labor is recognized, whose risks are hidden, and whose benefits are ultimately measured.

Algorithmic Epistemic Bias and Cultural Erasure

These environmental and economic issues intersect with deeper epistemic concerns. Despite major investment, commercial AI systems remain strongly oriented toward English-language data and Western cultural frameworks (Bender et al., 2021). As a result, they often perform poorly in other languages, misinterpret culturally specific concepts, and marginalize non-Western ways of knowing (Birhane et al., 2022). Head and colleagues (2024) show that these biases produce quality failures in AI outputs that disproportionately affect historically marginalized groups—outcomes that conflict with evaluation’s commitments to equity and justice.

From a decolonial perspective, such patterns reflect what Santos (2014) describes as epistemicide: the erosion or displacement of non-Western knowledge systems. For evaluators, epistemic bias is not only an inclusion problem; it also undermines the credibility and validity of evaluative judgments themselves. Until AI systems address these foundational issues, their ability to support transformational and culturally responsive evaluation remains limited.

Implications for Transformation-Focused Evaluation

These competing dynamics—AI’s potential benefits alongside contradictions with transformational values—create complex choices for evaluators committed to transformational agendas. Rather than prescribing universal answers, this article examines how these tensions manifest in practice on the African continent, and what they imply for evaluators working within transformational and decolonial commitments.

We begin by situating AI and evaluation within polycrisis conditions, then examine the intersections between MAE and MAAI as complementary efforts to recenter African agency, epistemologies, and governance in both evaluation and technology.

To illustrate both the potential and pitfalls of AI in evaluation, the core of the article explores intersections between MAE and MAAI. We use these movements to clarify practical opportunities, risks, and enabling competencies for responsible AI-enabled evaluation.

AI and Evaluation in the Age of Polycrisis

To understand the role of artificial intelligence (AI) within evaluation’s transformational imperative, we must situate both technology and evaluation practice within their broader social, political, and epistemic contexts. This requires examining the convergence of overlapping global emergencies and the evolution of both AI capabilities and evaluation approaches.

The term *polycrisis* refers to the confluence of interconnected emergencies that cannot be addressed in isolation. These include climate change, biodiversity collapse, economic inequality, political instability, and information disorder (Lawrence et al., 2024). Within this context, evaluation is being asked to support decision-making amid unprecedented complexity and uncertainty. The transformational imperative emerges as a response to these conditions, calling for evaluation approaches that can engage with systemic interdependencies rather than isolated program effects.

The Evolution of Contemporary AI

Artificial intelligence is “the tangible, real-world capability of non-human machines or artificial entities to perform, solve tasks, communicate, interact, and act logically in ways associated with biological humans” (Gil de Zúñiga et al., 2023). While AI research dates back to the 1950s, the past decade has seen rapid transformation. The 2017 introduction of the Transformer architecture (Vaswani et al., 2017) marked a decisive shift, enabling the generative AI systems we use today.

GenAI, including large language and multimodal models such as ChatGPT and Claude, represents AI’s transition from specialized instrument to general-purpose technology capable of creative and knowledge-intensive work (Papadimitriou & Manning, 2021). Its rapid diffusion has prompted fundamental questions about AI’s role across social systems, including evaluation.

Intersecting Trajectories

In this setting, AI introduces possibilities for addressing complexity as well as risks that may intensify existing uncertainties. Evaluators increasingly recognize AI’s potential to support analysis and learning, while also expressing

concern about its implications for epistemic integrity, accountability, and social justice.

The tensions outlined in the previous section—i.e., environmental costs, extractive labor arrangements, and epistemic bias—take on particular significance when viewed through the lens of polycrisis. If AI systems reinforce the very dynamics that contribute to interconnected global crises, their deployment in evaluation practice becomes deeply problematic. However, if AI can be developed and governed differently, it might support more responsive, contextually grounded, and equitable evaluation approaches.

The Shifting Sands of Evaluation

AI is not the only driver of shifts in evaluation. Recent scholarship documents evolving understandings of evaluator roles, debates about evaluation's purpose and beneficiaries, and sustained calls to decolonize practice (JMDE, 2023). These shifts are frequently framed through transformation-focused evaluation.

Transformational change refers to deep and fundamental changes in political, social, economic, ecological, and technological systems that give rise to new structures, norms, and ways of working (CIF, 2021). This orientation responds to three interrelated drivers: the urgency of polycrisis demanding engagement with intertwined environmental and social breakdown; the uptake of complexity theory challenging linear causality models; and pressure from funders seeking evidence of transformational change (Chaplowe & Hejnowicz, 2021).

Chaplowe and Hejnowicz (2021) identify persistent constraints on evaluation's transformational potential, including fixation on projects, timeframes, metrics, and compliance-driven accountability. These limitations are further intensified by weakening information infrastructures, mis- and disinformation, declining trust in evidence and science (Štětka et al., 2024), politically motivated defunding of research institutions, and removal of public data (White House, 2025). These dynamics shape the conditions under which AI-enabled evaluation is emerging.

Early reflections on AI uptake within evaluation illustrate this ambivalence. Writing 1 year after the release of ChatGPT, Raftree and Tilton (2023) observed strong enthusiasm among evaluators alongside limited understanding of what emerging AI systems can, cannot, or should not do for evaluation practice. This uncertainty persists. Nielsen and colleagues (2025) argue that within

data-driven knowledge economies, evaluation risks marginalization unless it develops interdisciplinary capabilities while retaining its social science foundations and contextual accountability. This tension between technological adaptation and evaluative integrity defines contemporary debates.

From a decolonial perspective, AI-enabled evaluation risks reproducing colonial patterns of data extraction and epistemic dominance, given that AI systems are largely designed, governed, and owned in the Global North, trained on data sets that marginalize Global South contexts, and deployed in ways that extract value without corresponding control or benefit (Birhane, 2023; Salami, 2024).

While a growing body of literature examines AI in evaluation and transformation-focused evaluation separately, limited work explores their intersection through decolonial and regionally grounded lenses. Next we explore this gap by examining how MAAI and MAE might inform more equitable and contextually responsive AI-enabled evaluation practice.

AI, Evaluation, and the Transformational Imperative on the African Continent

To ground our analysis, we examine AI, evaluation, and the transformational imperative in Africa, where nations are actively repositioning themselves relative to emerging AI technologies. Rapid AI uptake across African contexts is reshaping various sectors, including evaluation, necessitating critical reflection on implications and contextual adaptation. Understanding this phenomenon requires avoiding technological determinism—i.e., treating technology as an autonomous force with independent agency. AI's deployment in Africa results from decisions by technology companies, governments, development organizations, investors, and local actors pursuing diverse and sometimes conflicting interests (CIPIT, 2025).

While some projections estimate AI's potential contribution to Africa's economy at up to \$2.9 trillion by 2030 (Humeau & Deshpande, 2024), such claims warrant scrutiny, particularly regarding how benefits and costs are distributed. AI development across African countries remains uneven, shaped by differences in policy frameworks, investment levels, infrastructure readiness, and governance capacity (CIPIT, 2025). For evaluators, this unevenness presents the need to interrogate AI's embedded assumptions, value systems, and epistemic biases rather than adopting tools uncritically. This is especially important

where dominant AI systems may misalign with African worldviews, knowledge practices, and institutional realities.

The Relevance of Made in Africa AI for Evaluators

MAAI and MAE share an epistemic ambition: decolonizing both technology and evaluation practice. If evaluators are to apply AI for their work in Africa, it must fit within MAE paradigms—in essence, it must be Made in Africa AI.

The integration of AI into evaluation is inherently political. Given developmental aid's history as a vector of colonization in the Global South (Mamdani, 1996; Chiba & Heinrich, 2019; Becker, 2020), evaluators must examine not only functionality but the assumptions embedded in AI systems. Centering African agency and ownership could provide a transformational alternative to Western-dominated AI—models that are less extractive, more relevant, and more capable of supporting navigation through polycrisis.

What is Made in Africa Evaluation?

Made in Africa evaluation represents both a political response to Western epistemological dominance in evaluation and a systematic effort to transform foundational knowledge systems and power structures governing international development evaluation practice (Masvaure & Motlanthe, 2022).

African-rooted evaluation refers to evaluation approaches, frameworks, methods, and tools informed by African philosophies, Indigenous knowledge systems, cultural values, and worldviews (Boadu, 2023). It emphasizes integration of relational ontologies, epistemologies, and axiologies derived from African traditions, including Ubuntu, Afrocentric paradigms, and ethnophilosophy (Chilisa et al., 2016, Chilisa 2019; Omosa et al., 2021). These approaches prioritize community participation, collective well-being, and contextual relevance, aiming to address power asymmetries and elevate voices of marginalized groups. Fish (2022) identifies key characteristics of African-rooted evaluation:

- **Philosophical foundations:** Grounded in African philosophies like Ubuntu, which emphasize interconnectedness, collective responsibility, and relational ethics.
- **Indigenous knowledge systems:** Incorporates oral traditions, proverbs,

storytelling, rituals, and other cultural practices as tools for evaluation.

- **Community participation:** Engages local communities, traditional leaders, and stakeholders throughout the evaluation process to ensure inclusiveness and ownership.
- **Decolonization and indigenization:** Challenges Western-centric evaluation practices by promoting African-centered methodologies and frameworks.
- **Culturally responsive:** Ensures evaluations are sensitive to African cultural contexts, values, and norms.
- **Transformative goals:** Aims to contribute to social justice, equity, and sustainable development by addressing systemic injustices and promoting African agency.

What is Made in Africa AI?

Made in Africa AI (MAAI) advocates for AI development and deployment by, with, and for African communities. Drawing on a qualitative landscape study conducted by the MERL Tech Initiative (MTI), a practitioner-led definition of MAAI has emerged. This definition emphasizes African agency, ownership, linguistic and cultural grounding, stakeholder participation across AI lifecycles, and alignment with African-determined ethical and regulatory frameworks (Magodo-Matimba, 2025a).

MAAI treats Indigenous knowledge systems—including oral traditions, community wisdom, and local ecological knowledge—as legitimate and valuable data sources. Rather than being dismissed as anecdotal, these forms of knowledge are recognized as authoritative and relevant for AI training and application. As one African MERL practitioner noted, MAAI emphasizes “very localized and truly meaningful efforts that are responsive and nuanced towards the African context as unique and diverse” (Landscape Study, KII Participant 8).

The Intersection of MAAI and MAE

For African evaluators engaging with AI, adopting MAAI principles represents more than methodological evolution; it signifies recentering African agency, aspiration, and interpretive authority. African-rooted evaluation can contribute to a transition out of the polycrisis because it embeds more connected, less extractive values and practices. The argument is that for AI to serve transformation-focused evaluation in African

contexts, MAAI must align with MAE paradigms. This requires:

- **African agency and ownership:** Africans determine what works for African contexts, leading development and deployment decisions.
- **Epistemological pluralism:** AI systems recognize and incorporate multiple knowledge systems, particularly Indigenous African knowledge.
- **Participatory design:** Communities codevelop AI tools rather than being passive recipients.
- **Contextual grounding:** AI applications address African-identified priorities within African cultural and institutional frameworks
- **Transformation-focused:** Technology integration supports, rather than undermines, social justice and decolonial goals

This alignment could provide transformational alternatives to Western-dominated mainstream AI, ultimately offering AI models and applications that are less extractive, less colonial, and more capable of supporting navigation through polycrisis transitions.

The Logic of Decolonized AI in Evaluation

Understanding how MAAI might serve transformation-focused evaluation requires

unpacking the underlying logic, which rests on the premise that technologies encode epistemologies and power relations. Tools designed within colonial knowledge systems are likely to reproduce colonial outcomes, even when applied with decolonial intent.

Decolonizing AI therefore requires African-led processes of design, governance, and deployment that center African priorities and ways of knowing. When aligned with MAE principles, such AI systems may enhance analytical capacity, broaden participation, and generate contextually grounded evaluative knowledge without reproducing extractive or exclusionary practices. This logic rests on assumptions that warrant continued empirical scrutiny, including whether AI can be meaningfully decolonized and whether African-led governance consistently produces more equitable outcomes.

How MAAI Could Enhance MAE in Practice:

Illustrative Representation

Transformation-focused evaluation demands approaches capable of engaging with complexity, centering marginalized voices, and supporting systemic change. Evaluators increasingly interpret large, diverse, and often unstructured data. In this context, MAAI could enhance MAE practice in several ways that align with these transformational imperatives (see Table 1).

Table 1. Ways That MAAI Could Enhance MAE Practice Aligned with Transformation Principles

Role of an AI System	Output	Enhancement to evaluation practice	Transformation-focused principles of evaluation supported
MAAI systems designed to process evaluation data and recognize African languages, cultural concepts, and knowledge structures.	MAAI system analyzing evaluation interviews conducted in local African languages.	Potentially preserve cultural nuances that English-language AI systems miss or distort, enabling deeper understanding of community perspectives.	Justice (centering marginalized voices and ways of knowing); context (culturally situated interpretation); power shift (supporting local ownership over meaning-making).
MAAI tools designed to support real-time data synthesis.	MAAI systems process ongoing feedback from community health workers across multiple languages and regions,	Maintaining participatory engagement principles while ensuring community ownership of data and interpretation.	Complex systems (responding to emergence and non-linearity); detective (integrating plural

Role of an AI System	Output	Enhancement to evaluation practice	Transformation-focused principles of evaluation supported
	identifying emergent patterns that inform rapid program adjustments.		evidence and signals over time); purpose (learning-oriented, adaptive use of evaluation for transformation).
MAAI enabling broader participation in evaluation processes without sacrificing depth.	Voice-based AI interfaces in local languages could enable elders and community members to contribute evaluation knowledge through oral traditions.	Scaling participatory processes and transcending literacy barriers that often limit participation.	Power shift (broadening who participates and who leads knowledge generation); justice (epistemic inclusion and voice); context (valuing oral traditions and local communicative practices).
MAAI systems attuned to local contexts	An evaluation tracking agricultural interventions could integrate traditional ecological knowledge with climate data, crop yields, and farmer feedback to provide contextually relevant insights.	Increase evaluation responsiveness to emergent patterns through insights that neither traditional evaluation nor Western AI alone would generate.	Complex systems (integrating interacting dynamics across ecological and social systems); context (locally grounded relevance); detective (triangulating diverse knowledge forms).

Note. Inspired by the principles of transformation-focused evaluation as explained by Buckton et al. (2025). These possibilities remain largely theoretical, requiring empirical validation through carefully designed pilots and evaluations.

Emerging Use Cases: Findings from our Landscape Study

Understanding how MAAI might serve transformation-focused evaluation requires examining current realities. The MERL Tech Initiative conducted a landscape study in 2025 to understand the needs, gaps, and priorities of evaluation practitioners in Africa, recognizing that technological adoption cannot be separated from questions of power, epistemology, and justice (Magodo-Matimba, 2025b).

The findings reveal gaps between transformational aspirations and current practice, documenting barriers preventing AI from supporting transformation-focused evaluation and risks that AI adoption might actively undermine transformational principles. The study centers African practitioner perspectives and contributes

practical insights to inform training programs and support systems across the continent.

Methodology: MAAI Landscape Study

The landscape study employed a qualitative approach centered on semi-structured interviews to gain insights into capacity strengthening approaches and measurement frameworks for AI-MERL activities (Magodo-Matimba, 2025). Participants were selected from seven African nations (South Africa, Egypt, Nigeria, Kenya, Zimbabwe, Burkina Faso, and Uganda) plus Canada and the United States for comparative perspectives. The sample comprised MTI's AI + Africa Working Group members, civil society organizations, AI Africa specialists, and MERL sector experts. Comprehensive secondary data analysis complemented primary data collection

through systematic review of institutional reports, academic literature, and policy documents.

It addressed questions including: What knowledge gaps exist regarding AI among MERL practitioners? What do MAAI and MAE look like? How equipped are current AI tools for African contexts? And how might partners collaborate on advancing this work?

Defining Made in Africa AI for MERL

Magodo-Matimba (2025) presents MAAI as a multidimensional framework that transcends technical specifications to embody decolonial aspirations and contextual imperatives central to transformation-focused evaluation practice. Building upon the MAE movement, which itself responds to transformational imperatives by challenging Western epistemological dominance, the framework is characterized by three core commitments. First, community-driven participatory methods that prioritize Indigenous definitions of success over Western-centric metrics, rooted in responsiveness to African contexts in all their diversity. As one MERL sector expert articulated: “It shouldn’t be subsumed or consumed by the notion of producing skills that can just be used by the West to further their progress.... How do we use these new technologies to support the transformation that’s needed for Africa?” (p. 27). Second, alignment with Ubuntu principles emphasizing fairness, transparency, and accountability, with communities participating in design, development, and deployment. Third, avoidance of repeating colonial harms, ensuring AI accommodates different cultures and languages while remaining viable beyond external funding dependencies.

Current State of AI Adoption by African Evaluators

This section summarizes key findings from the landscape study (Magodo-Matimba, 2025) on how African evaluators are currently engaging with AI in MERL practice, highlighting prevailing adoption patterns, capacity constraints, and structural disconnects that shape its transformational potential.

Limited Implementation Patterns. African evaluation practitioners’ use of AI for MERL remains in early stages, characterized by basic applications, exploratory use, and significant knowledge gaps rather than sophisticated MERL-specific implementations. This limited adoption

pattern has implications for evaluation’s transformational potential. The landscape study suggests that the evaluation community is primarily in a familiarization phase, grappling with fundamental questions about AI’s role and relevance. As one AI in Africa Working Group member observed, “For many people AI is just used for writing, for reports, for emails, but they don’t know that it can be a huge brainstorming tool, and it can be a great tool to manage content to enhance messaging and enhance creativity” (p. 25). African evaluators are primarily engaging with general-purpose tools like large language models for text generation, rather than deploying specialized applications designed for evaluation processes such as automated data analysis, natural language processing of qualitative data, or predictive modeling for program outcomes.

Capacity Landscape. Formal training in AI evaluation and social impacts remains scarce among evaluation practitioners. As one MERL practitioner and AI in Africa Working Group member noted, “Very few have formal training [in AI evaluation and social impacts]; we in the evaluation [sector] are just getting used to AI” (p. 24). The capacity gap becomes more significant when considering the dual competencies required: Evaluators increasingly need both usage ability as an essential skill and the ability to evaluate AI itself as a technology.

Africa’s positioning as predominantly AI deployers and not developers positions the continent as consumers rather than creators of AI solutions, reinforcing training deficits (Magodo-Matimba, 2025, p. 24). Educational institutions appear inadequately equipped to address these gaps, with participants questioning the AI acumen of university graduates regarding machine learning, data visualization, and AI leverage (p. 24).

This highlights the need for an environment of informed experimentation grounded in a comprehensive understanding of its implications for evaluation quality, ethical practice, and cultural appropriateness.

The Language Technology Disconnect. While African language processing initiatives led by organizations including Data Science Nigeria, Data Science for Social Impact, Masakhane, Lelapa AI, and EqualyzAI represent important efforts to systematically include African languages in AI data and models, these initiatives have not translated into widespread MERL practitioner adoption. Donor-imposed language requirements continue mandating that M&E processes ultimately be reported in English, French, or Portuguese,

perpetuating colonial language dependence despite technological advances that could enable vernacular language evaluation (Magodo-Matimba, 2025). This disconnect between what is technically possible and what is practically implemented reflects broader patterns of limited engagement with AI tools.

Structural Barriers to Meaningful AI Integration

The MAAI landscape study reveals multilayered barriers impeding AI integration within African evaluation contexts, extending beyond technical capacity to encompass infrastructure, institutional, and contextual dimensions. Understanding these barriers is critical for the transformational imperative, because they reveal how current AI systems may actively undermine rather than support the deep systemic changes transformation-focused evaluation seeks to enable.

Tool Unsuitability. Current AI tools are fundamentally unsuitable for African evaluation practice due to systemic biases, inadequate language support, and training data misaligned with African realities. This unsuitability directly contradicts transformation-focused evaluation principles: tools that invisibilize African realities cannot support the epistemic pluralism, contextual grounding, and decolonial practice that transformation-focused evaluation demands.

- **Information retrieval failures.** At the most basic level, practitioners encounter significant barriers. They are forced to add precise country or regional identifiers to obtain marginally relevant results, a strategy that yields limited success. As one AI in Africa Working Group member explained, “They still tell you every time you have to go in and really specify. Give me something South African. Give me something Zimbabwean, or give me something African, and sometimes it still doesn’t get it right” (p. 32). Another participant reinforced, “When you ask specifically, ‘Can you find me any literature on research particular[ly] in Africa[?],’ It doesn’t come up at all ... it should be representational.... But it’s not there at all” (p. 33).

These experiences reveal ingrained systemic privilege of data-rich Western contexts that deprioritize and invisibilize African realities. When African voices, perspectives, and epistemologies are absent from training data sets, tools reproduce

Global North paradigms at the expense of African realities (Magodo-Matimba, 2025).

- **Sectoral application limits.** The agriculture sector demonstrates more advanced AI integration, with government applications where farmers photograph plants for disease or nutrient deficiency identification. However, these advances face fundamental barriers. As one MERL practitioner and AI in Africa Working Group member described:

We struggled with capacity in terms of storage of data, because you need maybe some data warehouses that are big. You also need lots of data to actually effectively train this. These applications actually end up getting more data from other countries where our climate isn’t as similar... It means that in the meantime you’ll be getting wrong conclusions or evaluations. That cuts across all sectors in terms of data, whether it’s health or mining, whatever sector. (p. 33)

Language Infrastructure Deficit. Language exclusion represents a particularly critical dimension of tool unsuitability, manifesting across multiple interconnected challenges.

- **Data set gaps.** Weak language resources, rather than model choice alone, constrain AI utility for MERL in African contexts. The exclusion of African languages from AI data sets risks creating compounding silence in evidence systems, where communities become invisible because their languages are not represented. As one Africa AI expert explained:

In natural language processing, [we need to have] datasets that are in languages that are specific to the problem that the system is trying to solve. If it’s an education system, it’s datasets that can be trained to respond to an education problem. Those datasets are missing. (p. 29)

- **Translation challenges.** Key technical terms, especially in health and education, lack reliable equivalents in African languages, reinforcing dependence on colonial languages. One NLP developer and AI in Africa Working Group member described attempting to translate sexual and reproductive health and rights terminology into Yoruba and other African languages as very difficult, noting that a translator tool they developed could not perform well because most African languages are not easily available to interpret (p. 30).

- **Professional communication dilemmas.** As Marivate et al. (2025, as cited in Magodo-Matimba, 2025) note:

When a language isn't in the data, its speakers aren't in the product, and AI cannot be safe, useful or fair for them. They end up missing the necessary language technology tools that could support service delivery. This marginalises millions of people and increases the technology divide. (p. 30)

Data and Digital Infrastructure Challenges. Digitalization emerged as a foundational challenge. With MERL digitalization lagging across Africa, many evaluation processes remain analog, preventing meaningful AI integration regardless of tool availability. Data scarcity compounds this: AI tools function effectively only when trained on data reflecting the realities and languages of the people they serve, yet such data are often missing, poorly structured, or scattered across multiple sources—resulting in erroneous conclusions across sectors.

Policy and Governance Gaps. While there may be “government buy-in because [AI] started to be everywhere,” there remains a lack of “policy frameworks that adopt and integrate use of AI” with actionable implementation strategies (Magodo-Matimba, 2025, p. 24–25). The disconnect between policy development and implementation is stark. As one participant explained:

It's so easy to draft a policy in a day and a night. You can have the policy paper and also have an action plan. But implementing and enacting this action plan is completely different. (p. 25)

Progress is further hindered by fragmented, non-African-centric regulatory frameworks that external actors readily exploit in the absence of a unified continental policy voice.

Forward-Looking Risks

Beyond current challenges, practitioners identified four interconnected risks for AI in African MERL: misaligned systems, weak governance, extractive data practices, and operational fragility.

Cultural Misalignment

Participants consistently identified cultural bias as the most pressing risk, arguing that current AI systems are designed primarily for Western contexts and fail to adequately represent African

languages, cultures, and social dynamics. Many tools are trained on non-African data and assumptions, which nudges evaluators toward imported theories and undermines authentic framing of a Made in Africa approach. As one MERL practitioner and AI in Africa Working Group member articulated:

AI is not using our data. A lot of what you get is feedback based on Western cultures, Western nuances, Asian nuances. That's a big risk. Especially if you're talking about 'Made in Africa Evaluation,' you end up gravitating towards those theories, evaluation theories and approaches that are already set, and from the West or from other places. We lose the Made in Africa because we need a tool to use, and the only tool available or the only tools available are not made by Africans for Africans, specifically.” (p. 35)

Data Extraction and Commercialization

Perhaps the most pressing concern relates to data ownership dynamics. While African researchers and communities generate vast amounts of language data, funders often mandate open licenses with no restrictions, enabling external actors to commercialize data sets and sell products back to African governments. Participants described a pattern where African data is extracted through open licensing requirements, only to be commercialized by external entities who then sell AI products back to African governments and organizations at premium prices. This extractive cycle undermines African data sovereignty and positions Africa as a consumer rather than cocreator in AI innovation, creating a neocolonial dynamic that perpetuates dependency on foreign technology providers exploiting the very data that Africans generate openly.

AI in Africa and the Transformational Imperative: From Theory to Practice

As artificial intelligence reshapes evaluation practice globally, the imperative for context-specific, decolonial approaches becomes increasingly urgent. The journey toward genuine MAAI praxis—one that parallels and extends the principles of MAE—is underway, but obstacles remain, including infrastructural underresourcing, uneven skills distribution, gender disparity, the ongoing threat of data extractivism (Adams, 2022; MERL Tech, 2022; Sub-Saharan Africa AI Report,

2024), and the difficulty of building and launching African LLMs. Deliberate approaches to ethical vigilance, community-partnered research, and investment in African capacity, including human, technical, and epistemic, can help make technology an enabler of evaluation justice rather than a new agent of exclusion.

The landscape study findings validate that AI in African evaluation must be designed, governed, and assessed according to Indigenous knowledge frameworks and local contexts, while revealing specific gaps between principle and practice.

Translating these principles into action requires examining concrete modalities for operationalization: technical solutions for AI infrastructure, approaches for community-centered development, and systemic frameworks for addressing power differentials in governance and ownership.

Finding Solutions to Advance Made in Africa AI for MERL

The landscape study demonstrates that current AI adoption patterns in African evaluation contexts fail to support, and may actively contradict, transformation-focused evaluation principles. The following sections explore how technical development, community-centered implementation, and systemic frameworks can align AI with transformational imperatives.

Building African Large Language Models: Technical Pathways Forward. Despite growing potential—with over 2,400 AI-focused companies operating across sub-Saharan Africa—significant infrastructural barriers persist, including poor connectivity, unreliable electricity, and high technology import costs (Oxford Insights, 2024). The integration of AI in evaluation must address ethics and equity at the foundational level, as LLMs “hold immense promise, but can also intentionally, or unintentionally, do harm” (Greenstein & Cho, 2025, p. 56).

The benefits of LLMs remain largely unrealized for Africa’s low-resource languages. Hussen et al. (2025) analyzed African language coverage across multiple AI models, revealing stark inequities: Only four languages (Amharic, Swahili, Afrikaans, and Malagasy) received consistent support, while over 98% of African languages remained unsupported. This has direct implications for transformation-focused evaluation: Approaches seeking to center marginalized voices cannot rely on AI systems that systematically exclude most African languages and perpetuate Western epistemological dominance.

The researchers recommend tailored small language models focused on core tasks like translation, speech recognition, and text classification—models that can be built without vast data sets or expensive infrastructure. Professor Mpho Primus argues these represent Africa’s best path forward, though African government investment is crucial (Magodo-Matimba, 2025).

Operationalizing Community-Centered AI: From Principle to Practice. While technical solutions address infrastructural dimensions, the transformative potential of these technologies depends on who shapes their development. MTI’s landscape study established that MAAI must embody Ubuntu principles and participatory design, the challenge is operationalizing these commitments.

Decolonizing research requires positioning communities as collaborators with agency rather than passive subjects (Wallerstein et al., 2013; Reid et al., 2021). Youth and marginalized communities must be substantively involved in participatory annotation, cocreation of stories, and contextual interpretation of AI-driven analytics.

Capacity development must center on Africa’s development rather than serving external interests. As one participant emphasized, “It shouldn’t be consumed by the notion of producing skills that can just be used by the West... to produce more evidence for others to use rather than for Africa’s own progress” (Landscape Study, KII Participant 3). However, organizations often adopt decolonizing frameworks as superficial labels without substantive change.

Interrogating Power and Addressing Extractivism Through Systems Thinking. MTI’s landscape study documented how funders’ open licensing mandates enable external actors to commercialize African data sets and sell products back to African governments, creating neocolonial dependency. This pattern reflects broader digital extractivism—i.e., a form of extraction made possible by digitization and exacerbated through borderless capitalism, mirroring colonial practices of wealth and resource accumulation (Iyer, 2023; Coleman, 2019). Data collection and processing by major technology platforms mirrors historical patterns of colonial exploitation, creating contemporary “data colonialism” that perpetuates core-periphery dynamics where resources flow from the Global South to enrich technology companies in the Global North (Banya, 2025; Luo, 2025).

Addressing these patterns requires analytical frameworks that interrogate power and agency. When examining emerging technology development and adoption within the transformational imperative framework, analysis must move from project thinking to systems thinking, from theory of change to theory of transformation, and from evaluator independence and neutrality to acknowledging interdependence (Patton, 2020; van den Berg et al., 2019). These shifts are not merely conceptual but represent the fundamental reorientation transformation-focused evaluation requires.

Systems thinking reveals that the technical challenge of building African LLMs, the governance challenge of data sovereignty, and the capacity challenge of African-led development are fundamentally interconnected. Addressing one dimension without the others perpetuates extractive patterns under new technological guises.

Fortunately, a road map for this transformational shift already exists. The conceptual framework for translating theory into practice in AI for African evaluation has been established through the MAE scholarship. This body of work calls for a departure from one-size-fits-all technological approaches imposed through a framing of Africa as merely an adopter and end user. Instead, it advances the development of AI solutions grounded in African epistemologies, values, and governance systems. This ultimately positions Africa as a cocreator of technologies shaped by shared normative commitments.

From Blueprint to Implementation: Competencies and Pathways for MAAI

The blueprint for transformational AI in African evaluation exists within the MAE scholarship. The landscape study validates this while revealing implementation gaps. Translating principles into practice requires developing critical competencies and advancing pathways for systemic change.

Essential Competencies for Transformational AI Practice

Based on MAE and MAAI approaches, the following four interconnected competencies are critical for aligning AI in African evaluation with the transformational imperative.

- **Power dynamics and systemic analysis.** Evaluators must recognize how AI perpetuates colonial dynamics when power and resources

concentrate in Western corporations. As the landscape study documented, funders' open licensing mandates enable external actors to commercialize African data sets and sell products back to African governments, creating neocolonial dependency. Evaluators need the capacity to analyze "data extractivism"—i.e., how profits flow away from data-generating communities—alongside understanding of extractive labor chains, environmental costs, and how AI excludes non-Western knowledge systems. This analysis should inform decisions about whether and how to use AI for evaluation.

- **Infrastructure and contextual realities.** Evaluators must grapple with material conditions shaping AI possibilities. The landscape study revealed how poor connectivity and unreliable electricity serve as fundamental barriers, contributing to data sparsity and low-quality outputs. Current AI tools fail to retrieve African-relevant information, produce culturally misaligned outputs, and exclude African languages. These deficiencies fundamentally undermine their utility for evaluation practice.
- **Resistance and refusal.** Evaluators should develop the capacity to say no to harmful AI, recognizing that some applications are fundamentally opposed to transformational values. Building strategic resistance implies knowing when and how to reject technologies that conflict with these values, and represents a core professional competency, not a deficit.
- **Flexibility and adaptive learning.** AI's rapid evolution makes flexibility essential. The landscape study revealed that African evaluators are in a familiarization phase with limited formal training. Addressing this requires ongoing learning that goes beyond mastering specific tools to developing constantly evolving competencies

Critical Pathways for Systemic Change

Beyond individual competencies, realizing MAAI requires coordinated action across technical, participatory, and systemic dimensions:

- **Technical development.** Investment in small language models and specialized SLMs that serve African languages and contexts, supported by community-driven data collection, script standardization, and culturally aware evaluation metrics. As research demonstrates, these smaller, more

agile models can be built to fit African contexts without requiring vast data sets or expensive infrastructure. This requires African government investment and continental coordination to avoid fragmented efforts external actors can exploit.

- **Participatory implementation.** Moving beyond superficial adoption of participatory language to genuine community cocreation throughout AI development and deployment. This operationalizes the Ubuntu principles and participatory design commitments established in MAAI frameworks. It includes engaging youth and marginalized communities in participatory annotation, story cocreation, and contextual interpretation of AI-driven analytics, ensuring AI systems reflect lived experiences rather than imported frameworks. As landscape study participants emphasized, this requires moving beyond tokenistic consultation to substantive involvement where communities lead and design frameworks reflecting Indigenous African perspectives.
- **Systemic transformation.** Shifting from viewing AI adoption as a technical capacity gap to recognizing it as requiring transformation of power relationships, funding structures, and knowledge production systems. This demands interrogating whose purposes AI tools serve, ensuring African data sovereignty, and building sustainable African-owned AI infrastructure beyond external funding dependencies. It requires moving from project thinking to systems thinking, from theory of change to theory of transformation, and from evaluator independence to acknowledging interdependence (Patton, 2020; van den Berg et al., 2019).

Future Outlook

The future of evaluation will include AI whether we embrace it or resist it. Our imperative is to actively shape AI development to align with our values, creating space for those who resist applications that contradict these foundations. The choice is not whether to engage with AI, but how to engage in ways that honor commitments to transformational change and decolonial practice.

MAAI represents more than technical adaptation; it offers a pathway for evaluation to engage with interconnected crises through approaches embodying the values necessary for navigating them. By prioritizing African epistemologies emphasizing interconnectedness and collective well-being, resisting extractive

practices, and building local ownership rather than dependency, MAAI demonstrates how evaluation can contribute to rather than merely document responses to global challenges. The competencies outlined here—i.e., power analysis, contextual grounding, strategic resistance, community cocreation, and systems thinking—represent essential capacities for evaluation practice globally.

The journey toward genuine MAAI praxis requires ethical vigilance, community-partnered research, and investment in African human, technical, and epistemic capacity. The blueprint exists within MAE scholarship; the challenge is implementation while maintaining fidelity to core principles. Only through such intentional approaches can AI serve as an enabler of evaluation justice rather than a new vector of exclusion.

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