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Decolonising Artificial Intelligence: A Theoretical Framework of Epistemic Representation, Data Sovereignty and African Knowledge Systems in Machine Learning

NWOGBOJI Emmanuel Usulor[1], IGWE Emmanuel Sunday[2], OGAH Sunday Ogbo[3], ATOLAGBE Umar Kawu[4], Paul Idowu BAMIGBOLA[5]

[1,2,3,4,5] Veristzon Global Research Lab

ABSTRACT

The artificial intelligence (AI) systems that increasingly mediate knowledge, language and decision-making across Africa are trained on data in which Africa is marginal, built largely by institutions outside the continent, and organised by categories that African knowledge systems did not produce. Prevailing remedies (more African data and more African developers) treat the problem as one of missing data, and the literature lacks a framework that relates exclusion in data to the concepts and institutions that shape machine learning. This theoretical paper addresses that gap. Its objective is to develop a decolonial framework for AI, derive propositions on when AI systems represent rather than overwrite African epistemologies, examine the tension between data sovereignty and research openness, and set out a research agenda for African studies. Methodologically, it is an integrative, theory-building review. The population was peer-reviewed journal articles published between 2023 and 2026; a purposive sample of 42 articles was retained after each was verified against its publisher record and screened for retractions, corrections and expressions of concern. Findings were coded against provisional layers, compared across domains and synthesised abductively. The analysis distinguishes three layers at which coloniality operates: the data layer (whose texts, images and records are present), the categorical layer (whose concepts of person, property, kinship, privacy and knowledge the models encode) and the institutional layer (who builds, owns and governs). It argues that representation-only remedies act mainly on the first layer and so risk producing inclusion without representation. Seven propositions specify the limits of data inclusion, categorical overwriting, institutional capture, the role of local intermediaries, the sovereignty–openness tension, hollow sovereignty and the conditions for representation. The paper recommends community participation in defining problems and categories, decoloniality impact assessment in procurement and regulation, governed rather than closed data sharing, demonstrable sovereignty capacity, and African studies research that treats AI as an object of study rather than merely a tool.

Keywords: decolonial theory; artificial intelligence; epistemic justice; African knowledge systems; data sovereignty

1. INTRODUCTION

Artificial intelligence (AI) systems increasingly mediate how knowledge is found, how language is translated and how decisions are made across Africa: in newsrooms, public services, health systems, finance and education. Yet these systems are trained largely on data in which Africa is marginal, built mostly by institutions located outside the continent, and organised by categories that African knowledge systems did not produce. Generative models trained mainly on data-rich languages such as English reinforce dominant ideologies while leaving many African languages classed as "low-resourced" (Yin, 2025). When AI-driven media platforms serve Setswana, Tshivenda and Xitsonga speakers in South Africa, translation and voice-recognition error rates of roughly 30% to 42% have been reported (Aiseng, 2026). When the cultural values embedded in widely used language models are compared with nationally representative survey data, the models lean by default towards values common in English-speaking and Protestant European countries (Tao et al., 2024).

These findings are often read as a problem of missing data, and the remedies proposed follow from that reading: collect more African data, train more African developers and build more African datasets. This paper argues that such remedies are necessary but insufficient. They address *who is present* in the data while leaving unchanged *how* what is present is categorised and *who* builds, owns and governs the systems. Location shapes the development and governance of AI, and advanced countries and major technology firms hold substantial influence over the global AI cultures in which Africa participates (Obia, 2025). Data exploitation, infrastructure dependence and algorithmic bias are sustained not only by Big Tech but also by local intermediaries, including governments, technology elites and influencers (Effoduh, 2025).

A decolonial literature on AI has emerged, but it is dispersed across media studies, critical data studies, philosophy, law, health research and information science. Some contributions propose ethical frameworks grounded in Ubuntu (Mokoena, 2024; Ferlito et al., 2024; Sule, 2026); others document the political economy of digital colonialism (Okocha & Zoho, 2026; Atal & Mondliwa, 2025); still others examine data governance law and cross-border data flows (Singler & Babalola, 2025; Vásquez Callo-Müller & Sucker, 2026). What is missing is a framework that distinguishes the *levels* at which coloniality operates in machine learning and that explains why remedies at one level may leave the others intact.

This theoretical paper develops such a framework. It distinguishes three layers at which coloniality operates in AI: the *data layer* (whose texts, images and records are present), the *categorical layer* (whose concepts of person, property, kinship, privacy, health and knowledge the models encode) and the *institutional layer* (who builds, owns and governs). Its central argument is that the fashionable remedies of more African data and more African developers address the first layer while leaving the second and third largely intact, so that African knowledge can be *included* in AI systems and still be *overwritten* by them.

The paper has four objectives: (i) to synthesise recent peer-reviewed scholarship on AI, coloniality and African knowledge systems into a three-layer framework; (ii) to derive propositions about the conditions under which AI systems can represent rather than overwrite African epistemologies; (iii) to examine the tension between data sovereignty and the openness on which African AI research depends; and (iv) to propose a research agenda for African studies that treats AI as an object of study rather than merely a tool. It asks: At what levels does coloniality operate in AI? Why do representation-only remedies fall short? Under what conditions can AI systems represent African knowledge on its own terms?

2. LITERATURE REVIEW

2.1 CONCEPTUAL REVIEW

2.1.1 Coloniality and digital colonialism

Coloniality refers to patterns of power, knowledge and being that outlast formal colonial rule. *Digital colonialism* extends the concept to the control of digital infrastructure, data flows and platforms. Recent African scholarship warns against using the term loosely. Fosu (2025) argues that decolonial theory still matters for emancipation, but that it must centre the everyday realities of African societies, move beyond a binary of the Global North against Africa, and give a proactive rather than merely

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reactive account of African agency. Singler and Babalola (2025) similarly show that digital colonialism need not take the form of surveillance capitalism: Nigeria's data protection rules and border technologies reflect Northern norms, tools and practices filtered through local actors and interests, a *coloniality of knowledge* rather than simple extraction. Tse et al. (2025) extend the analysis to South–South relations, asking whether Chinese e-commerce platforms act as data colonisers in Kenya and documenting forms of consumer negotiation and resistance.

2.1.2 Epistemic representation and epistemic injustice

Epistemic representation refers to whether, and on whose terms, a community's knowledge is present in a system. Its failure is a form of *epistemic injustice*. Lassen et al. (2025) trace how data science practices produce silencing across the pipeline from data collection to deployment: biases in data collection yield models that mute minority voices, and deployed models further marginalise those groups in a self-reinforcing cycle. Clausen et al. (2025) show, in humanitarian settings, that representing local needs from a distance through big data and AI, which they term "datafied localization", reshapes context through the choices of those who collect data and risks reducing communities to data suppliers.

2.1.3 Data sovereignty

Data sovereignty refers to the right of a people or state to govern data about itself. The Indigenous data sovereignty movement provides the most developed account. Prehn et al. (2026) argue that AI will serve Indigenous communities fairly only if Indigenous data sovereignty and Indigenous-led governance are built in from the start, because data systems have historically functioned as instruments of colonial control and AI trained on them risks scaling those patterns. Sovereignty is, however, a contested term. Lehuedé (2024) finds that state and civil-society digital sovereignty frameworks only partly align with a decolonial option, while Grohmann and Barbosa (2026) show how large cloud providers redefine sovereignty as a purchasable product, "sovereignty-as-a-service".

2.1.4 African knowledge systems

African knowledge systems (often termed indigenous knowledge, IK) are described in recent reviews as local, community-owned, intergenerational, holistic and largely tacit (Dei et al., 2025). In Ghana, IK is held by healers, birth attendants, farmers, religious and clan leaders and chiefs, and is transmitted orally through apprenticeship, storytelling and cultural events, often without formal records (Dei, 2026). These properties matter for AI: knowledge that is oral, tacit, relational and held by custodians is precisely the knowledge least likely to appear in machine-readable corpora, and the most likely to be distorted when it does.

2.2 THEORETICAL REVIEW

Five theoretical perspectives inform the framework.

Decolonial theory beyond the binary. Following Fosu (2025), the framework treats coloniality as a structure in which African actors also participate, rather than as something done solely to Africa by outsiders. This explains why the institutional layer includes local intermediaries (Effoduh, 2025) and why multiplex digital partnerships can widen African governments' room for agency despite lingering dependencies (Soulé, 2025).

Epistemic injustice. The epistemic-injustice tradition, applied to data science by Lassen et al. (2025), explains how exclusion at the data stage becomes structural through feedback. It grounds the distinction between being *present* in data and being *understood* by a model.

Encoding/decoding. Yin (2025) applies Stuart Hall's encoding/decoding model to AI language technology, arguing that meaning is encoded by designers working in data-rich languages and decoded by users who may accept, negotiate or oppose it. This perspective links the categorical layer to the agency of users.

Relational (Ubuntu) ethics. Ubuntu-based scholarship offers an alternative to individualist categories in AI ethics. Ferlito et al. (2024) argue that debates about responsibility for AI harms in healthcare have been shaped mainly by Anglo-American and European philosophy, and propose an Ubuntu-inspired view emphasising collective and forward-looking responsibility. Mokoena (2024) proposes a holistic Ubuntu AI ethics for South Africa, and Sule (2026) draws on Afro-communitarian thought for a culturally grounded framework of responsible adoption. In the

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framework, Ubuntu functions as evidence that the *categories* of AI ethics, and not only its data, are culturally specific.

Political economy of platforms and locationality. Obia's (2025) "politics of locationality" explains how the geographic location of AI development reproduces structural disadvantage for Africa. Together with research on AI supply chains (Muldoon et al., 2025; Le Ludec et al., 2023), it grounds the institutional layer: where AI is built, and by whom, shapes who captures value and who sets the agenda.

2.3 EMPIRICAL REVIEW

2.3.1 The data layer: presence and absence

Evidence of under-representation is consistent. Generative AI marginalises African languages through training-data imbalances rooted in postcolonial language politics and oral traditions (Yin, 2025), and South African languages show high translation and voice-recognition error rates on AI-driven media platforms (Aiseng, 2026). Historical records are also unevenly digitised: African archives are systematically underrepresented in global digitisation efforts, and AI models often lack training on African historical corpora, as case studies of records from Portuguese-colonised territories show (Błoch et al., 2025). Health research faces similar gaps, with institutions differing widely in data availability, computing capacity and training needs (Kiragga et al., 2025).

2.3.2 The categorical layer: whose concepts?

Evidence that categories, and not only data, are at stake comes from several fields. Language models' default cultural values are skewed towards English-speaking and Protestant European countries; prompting models to answer as a person from a given country improves alignment for many countries but not for all (Tao et al., 2024). In Ghana, privacy operates in a plural-legal context combining customary and state norms, with individual, mutual and collective dimensions of harm, so that claims of African "privacy myopia" misread locally grounded norms (Kadiri & Boamah, 2025). In Zimbabwe, audiences of an AI news presenter criticised its lack of emotion and its accent, which the author reads as a call to decolonise and localise newsroom AI (Ndlovu, 2024). In the ethics of healthcare AI, an Ubuntu perspective reframes responsibility as collective rather than individual (Ferlito et al., 2024).

2.3.3 The institutional layer: who builds, owns and governs?

Institutional evidence points to concentrated control. Expert interviews indicate that the United States, China and Europe dominate AI investment and governance, while African leaders' achievements remain fragmented (Okocha & Zoho, 2026). South African fintech and chat-banking services, promoted as inclusive, tend to favour affluent customers, strengthen monopoly banks and platforms, and send customer data to foreign firms (Atal & Mondliwa, 2025). Mobile-learning interventions in sub-Saharan Africa are largely driven by funders and technology companies, which raises questions about who sets the research agenda (Banda & Chinkondenji, 2026). AI data work in Kenya and Uganda is organised through outsourcing firms in global supply chains (Muldoon et al., 2024), where low wages and insecurity persist despite "impact sourcing" claims (Muldoon et al., 2025). Regulation remains fragmented: a scoping review of 12 African countries found no AI-specific regulation in health, only relevant provisions in digital health, data protection, consumer protection and intellectual property law (Townsend et al., 2023). In public administration, AI raises questions about the integrity of decision support, inclusive decision-making and accountability in how platforms are funded and run (Plantinga, 2024).

2.3.4 Data sovereignty and openness

African research depends on data sharing, but sharing is fraught. Researchers in 16 sub-Saharan countries report individual fears and publication pressure, structural limits, weak recognition and the risk of being "scooped", ethical concerns about consent and commercialisation, and gaps in legal frameworks (Chabilall et al., 2024). Research ethics committee members report limited awareness of data protection laws and concerns about data transfer agreements, consent and stigmatisation (Cengiz et al., 2024). A systematic review of genomic data sharing in low- and middle-income countries identifies informed consent, data misuse, mistrust and inequity alongside legal questions of ownership and protection (Ekusai-Sebatta et al., 2026). At the continental level, the African Continental Free Trade Area's digital trade protocol gives greater weight to regulatory sovereignty and development goals than comparable

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Latin American frameworks (Vásquez Callo-Müller & Sucker, 2026).

2.3.5 Responses and alternatives

Several responses are emerging. Eke et al. (2026) find that existing AI impact assessments do not address coloniality, including who defines problems and whose knowledge counts, and propose a Decoloniality Impact Assessment embedded in existing frameworks. Ooko (2025), drawing on Rwanda's Mbaza chatbot and the Masakhane natural language processing (NLP) project, proposes a decolonial framework for communicating AI in public service grounded in epistemic justice and participatory communication. Sharma et al. (2026) use Afrofuturist speculative design with a Black-led community organisation to articulate counter-imaginaries centred on equity, epistemic justice and repurposing technology. Information science studies emphasise involving all stakeholders in IK digitisation projects (Chigwada & Ngulube, 2025).

2.4 GAP IN THE LITERATURE

Three gaps emerge. First, the literature identifies data scarcity, cultural bias and institutional concentration as separate problems but lacks a framework that relates them as layers of a single structure. Second, remedies are rarely assessed by the layer they address; as a result, the limits of data-inclusion strategies are under-theorised. Third, the tension between data sovereignty and research openness is documented in health and genomics (Chabilall et al., 2024; Ekusai-Sebatta et al., 2026) but has not been integrated into decolonial theories of AI. This paper addresses all three.

3. MATERIALS AND METHODS

3.1 RESEARCH DESIGN

The study is a conceptual, theory-building paper based on an integrative review of peer-reviewed literature; it collects no primary data. An integrative design suits a phenomenon that spans media and communication studies, critical data studies, philosophy, law, health research and information science. The analytic logic is abductive: mechanisms reported across studies were compared, patterns were identified, and a framework was constructed that accounts for them and yields testable propositions.

3.2 POPULATION AND SAMPLE

The population comprised peer-reviewed journal articles published between 2023 and 2026 on AI and coloniality, digital colonialism, epistemic injustice in data science, data sovereignty, African and Indigenous knowledge systems, Ubuntu and African AI ethics, and the governance of data and AI in Africa. Studies from other regions were admitted where they offered theoretical leverage (for example, on Indigenous data sovereignty, cultural bias in language models or digital sovereignty frameworks). Sampling was purposive, guided by the three layers of the emerging framework. The final sample comprised 42 articles (Table 1).

3.3 INCLUSION AND EXCLUSION CRITERIA

Studies were included if they (a) were peer-reviewed journal articles; (b) were published, in an issue or as advance online publications, between 2023 and 2026; (c) addressed one or more of the themes above; and (d) could be verified against the publisher's own record. Excluded were book chapters, conference proceedings (including proceedings papers published in journals), preprints, working papers, reports, theses, news items, and editorials, commentaries and opinion pieces; works published before 2023; and items whose bibliographic details could not be confirmed. Foundational decolonial and epistemological works published before 2023 are therefore discussed only as they are applied in the sampled literature.

3.4 DATA COLLECTION

Searches were conducted in October 2026 using scholarly web search and publisher platforms (including Sage, Cambridge University Press, Oxford University Press, Springer Nature, MDPI, PLOS, Frontiers and AOSIS). Search strings combined AI terms (*artificial intelligence*, *machine learning*, *large language models*, *algorithm*, *data science*) with concept terms (*decolonial*, *coloniality*, *digital colonialism*, *epistemic injustice*, *data sovereignty*, *indigenous knowledge*, *Ubuntu*, *data governance*, *data sharing*) and place terms (*Africa*, *Nigeria*, *Kenya*, *South Africa*, *Ghana*, *Global South*).

3.5 VERIFICATION AND BASES OF JUDGEMENT

Each candidate article was checked against its publisher page for title, authors, year, journal,

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volume, issue, pagination or article number, DOI and article type, and the page was inspected for retraction notices, corrections or expressions of concern. Of 65 candidate records that reached full-record verification, 42 met all criteria and 23 were excluded: 11 were editorials, commentaries, opinion pieces or similar non-research items; 9 could not be verified because the publisher page could not be accessed; 2 were conference proceedings papers; and 1 lacked a confirmable author list. Three included articles on AI data work had been verified in an earlier verification pass using the same procedure. None of the included articles carried a retraction or expression of concern; one carried a minor publisher correction adding a funder's logo, which does not affect its content. Pre-screening exclusions (items outside the date range or not published in journals) were not counted systematically, which is acknowledged as a limitation. Relevance was judged by whether a study reported evidence or argument bearing on at least one of the three layers or on the sovereignty–openness relationship.

Table. 1. Summary of source screening and verification

Stage / outcome	Records (n)
Candidate records reaching full-record verification	65
Excluded: editorial, commentary, opinion or similar	11
Excluded: publisher record not accessible for confirmation	9
Excluded: conference proceedings paper	2
Excluded: author list not confirmable	1
Included in final sample	42

Note. All included articles were confirmed against publisher records (October 2026). None carried a retraction or expression of concern; one carried a minor correction (addition of a funder logo).

3.6 DATA ANALYSIS

Analysis proceeded in three stages. First, the findings of each article were extracted and coded against the three provisional layers (data, categorical, institutional) and against reported remedies. Second, codes were compared across domains (language, media, health, finance, public administration, research governance) to identify convergent mechanisms, summarised in an evidence map (Table 3). Third, recurring mechanisms were formalised as propositions and integrated into a framework (Figure 1). Throughout, claims were tested against disconfirming evidence, for example findings that prompting improves cultural alignment for many countries (Tao et al., 2024) or that diversified digital partnerships widen African agency (Soulé, 2025).

3.7 VARIABLE MEASUREMENT

Although the paper is conceptual, its constructs are specified so that they can be measured in future empirical work. Table 2 presents operational definitions and indicators.

Table. 2. Constructs, operational definitions and proposed indicators

Construct	Operational definition	Proposed indicators
Data-layer coverage	Presence of African languages, records and populations in training and evaluation data	Share of training tokens/records by language and country; error rates on African inputs; digitisation coverage of African archives
Categorical fit	Degree to which a system's labels, objectives and metrics reflect the concepts of the communities it serves	Community-validated label schemes; agreement between system outputs and community judgements; presence of collective/relational categories (e.g., privacy, responsibility)
Institutional control	Location of ownership, finance, infrastructure and governance of an AI system	Share of African ownership and staff in decision roles; location of compute and data storage; funder origin; local accountability mechanisms
Governed sharing	Exercise of data sovereignty through enforceable terms rather than closure	Use of data-sharing agreements; culturally grounded consent; federated analysis; benefit-sharing provisions
Representation vs overwriting	Outcome for a community's knowledge in the system	Community assessment of fidelity; retention of local concepts in outputs; decoloniality impact assessment results

3.8 RELIABILITY, VALIDITY AND TRUSTWORTHINESS

Because the study is interpretive, rigour is addressed through trustworthiness criteria. *Credibility* was supported by verifying every source against its publisher record and by citing only what sources report. *Dependability* was supported by documenting search streams, criteria and screening outcomes (Section 3.5; Table 1). *Confirmability* was supported by seeking contrary evidence. *Transferability* is

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bounded: the framework draws mainly on sub-Saharan African evidence, supplemented by comparative work on Indigenous data sovereignty, and should be tested before being applied elsewhere.

3.9 AI USAGE DISCLOSURE AND OTHER DISCLOSURES

Generative AI tools (a large language model) were used to assist with literature searching, screening, checking bibliographic details against publisher records, and preparing an initial draft of the text and figure. All sources were checked against publisher records, and the author(s) reviewed, revised and take full responsibility for the content, interpretations and any errors. No AI tool is listed as an author. The study used only published literature; no human participants were involved and ethical approval was not required. All sources are listed in the references; no additional datasets or code were generated.

4. RESULTS AND DISCUSSION

4.1 RESULTS

4.1.1 Evidence map across the three layers

Table 3 summarises, for each layer, the mechanism through which coloniality operates, the typical remedy proposed and the evidence on that remedy's reach. The assessments are qualitative syntheses of the cited studies.

Table. 3. Evidence map: layers, mechanisms and the reach of remedies

Layer	Mechanism	Typical remedy	Evidence on reach
Data	Under-representation of African languages, archives and populations (Yin, 2025; Błoch et al., 2025)	More African data; inclusive datasets (Yin, 2025; Aiseng, 2026)	Improves performance; default cultural schema persists (Tao et al., 2024)
Categorical	Foreign concepts of privacy, responsibility and knowledge (Kadiri & Boamah, 2025; Ferlito et al., 2024)	Ubuntu/ relational ethics; localisation (Mokoena, 2024; Ndlovu, 2024)	Mostly proposed, rarely implemented; silencing self-reinforces (Lassen et al., 2025)
Institutional	External ownership, finance and agenda-setting (Obia, 2025; Banda & Chinkondenji, 2026)	More African developers; regulation (Townsend et al., 2023)	Value and data flow outward (Atal & Mondliwa, 2025); intermediaries co-produce (Effoduh, 2025)
Cross-cutting: sovereignty	Extraction vs dependence on sharing (Chabilall et al., 2024)	Data sovereignty laws; IDS (Prehn et al., 2026)	Effective when governed sharing (Kiragga et al., 2025); co-optable (Grohmann & Barbosa, 2026)

Note. Qualitative synthesis of the cited studies; not measured scores.

Three patterns stand out. First, evidence of exclusion is strongest and most quantified at the data layer, which helps explain why remedies concentrate there. Second, the categorical layer is visible mainly through what goes wrong when foreign categories meet African contexts: privacy reduced to individual consent where norms are collective and plural-legal, responsibility assigned to individuals where Ubuntu ethics assigns it collectively, and default cultural values that do not match African respondents. Third, the institutional layer determines which remedies are implemented and by whom. Data collection funded and organised from outside reproduces the agenda-setting it was meant to correct.

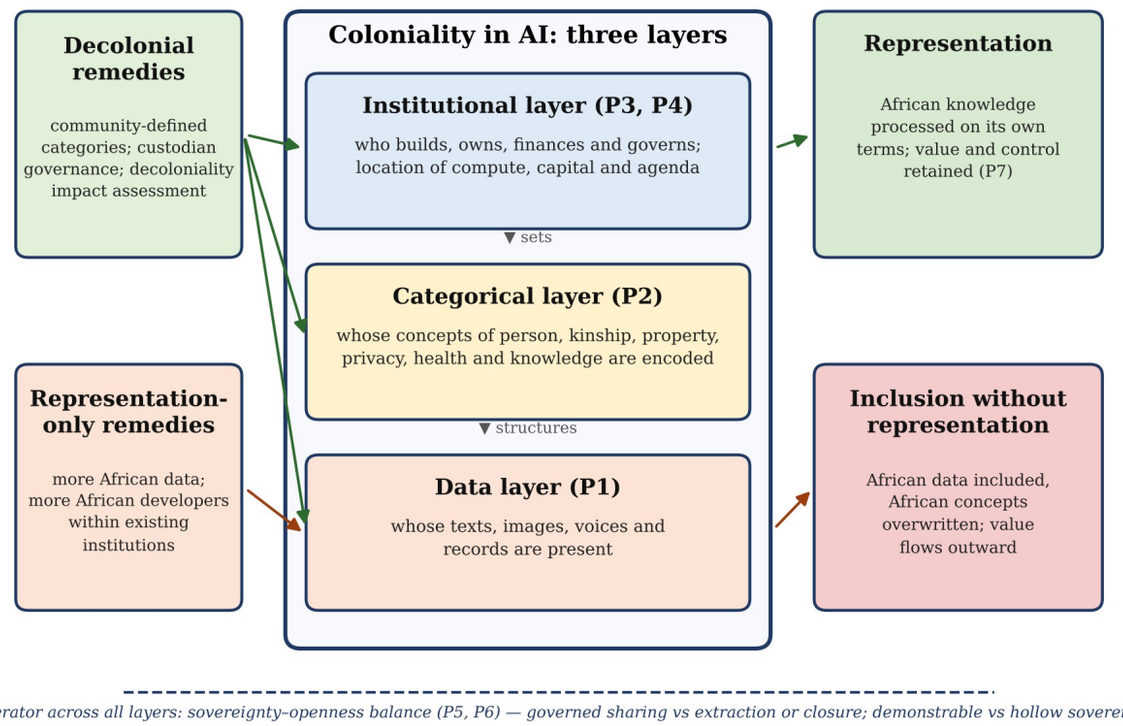
4.1.2 The three-layer framework

Figure 1 presents the framework. Coloniality in AI operates at three nested layers. At the *data layer*, the question is whose texts, images, voices and records are present. At the *categorical layer*, the question is whose concepts structure the data, labels, objectives and evaluation metrics: whose notion of a person, a family, property, privacy, health or truth the model encodes. At the *institutional layer*, the question is who builds, owns, finances and governs the systems and the infrastructure on which they run. Remedies act on particular layers. Representation-only remedies (more African data, more African developers inside existing institutions) act mainly on the data layer. Their outcome depends on the categorical and institutional layers above them: if those remain unchanged, African content is absorbed into foreign categories and governed by foreign institutions, an outcome the paper terms *inclusion without representation*. Representation, by contrast,

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requires that African communities shape categories and hold institutional power. A sovereignty–openness balance moderates all three layers.

Figure. 1. A three-layer framework of coloniality in artificial intelligence



Note. P1–P7 refer to the propositions in Section 4.1.3. Source: developed by the author(s) from the reviewed literature.

4.1.3 Propositions

Seven propositions follow from the synthesis.

Proposition 1 (data-layer sufficiency). Increasing African data in training sets improves performance on African inputs but does not by itself change the categories through which those inputs are interpreted. Limited training data drives high error rates for African languages, with community-driven data efforts showing promise (Aiseng, 2026), and inclusive datasets are proposed as a remedy (Yin, 2025); prompting likewise improves cultural alignment for many but not all countries (Tao et al., 2024). Yet such measures adjust performance without altering the default schema, which remains centred on the cultures that dominate the data.

Proposition 2 (categorical overwriting). Where African concepts differ structurally from those encoded in a system's labels, objectives and metrics, inclusion of African data leads to the translation of African knowledge into foreign categories rather than to its representation. Privacy norms that are collective and plural-legal (Kadiri & Boamah, 2025), responsibility that is collective (Ferlito et al., 2024) and knowledge that is oral and tacit (Dei, 2026) are all at risk of being overwritten when processed through individualist, written and decontextualised categories (Clausen et al., 2025; Lassen et al., 2025).

Proposition 3 (institutional capture). The more the infrastructure, capital and governance of AI are located outside Africa, the more the value created from African data and labour flows outward and the more the research agenda is set externally. This follows from the politics of locationality (Obia, 2025), data flows to foreign firms (Atal & Mondliwa, 2025), funder-driven agendas (Banda & Chinkondenji, 2026) and outsourced data work (Muldoon et al., 2025; Le Ludec et al., 2023).

Proposition 4 (intermediary co-production). Coloniality at the institutional layer is co-produced by local intermediaries, so that remedies targeting only foreign firms will be incomplete. Governments, elites and influencers sustain data exploitation and dependence (Effoduh, 2025), and Northern norms enter national law through local actors and interests

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(Singler & Babalola, 2025). Conversely, multiplex partnerships can expand agency (Soulé, 2025).

Proposition 5 (sovereignty–openness tension). Data sovereignty protects against extraction but, when implemented as closure, can starve African research of the data on which it depends; the tension is reduced when sovereignty is exercised through *governed sharing* (trusted agreements, culturally grounded consent, federated analysis and local control). This integrates evidence on researchers' fears and legal gaps (Chabilall et al., 2024; Cengiz et al., 2024), on mistrust and inequity in genomics (Ekusai-Sebatta et al., 2026), on federated models that keep data under local control (Kiragga et al., 2025), and on Indigenous-led governance (Prehn et al., 2026).

Proposition 6 (hollow sovereignty). Sovereignty claims that are not backed by the capacity to inspect, run and contest AI systems will be co-opted. Large providers repackage sovereignty as a service (Grohmann & Barbosa, 2026); sovereignty is often pursued through proxy tools such as certification, procurement and cloud governance (Raman & Nedungadi, 2026); and state frameworks may reproduce coloniality in economic and environmental domains (Lehuedé, 2024).

Proposition 7 (conditions for representation). AI systems are more likely to represent rather than overwrite African knowledge when affected communities participate in defining problems and categories, when knowledge custodians govern the use of their knowledge, and when decoloniality is assessed across the system lifecycle. Supporting evidence includes decoloniality impact assessment (Eke et al., 2026), participatory and relational communication (Ooko, 2025), community counter-imaginaries (Sharma et al., 2026), stakeholder involvement in IK projects (Chigwada & Ngulube, 2025) and community leadership of IK transmission (Dei et al., 2025).

4.1.4 A research agenda for African studies

The framework implies that AI should be studied by African studies as an *object* (a social, political and epistemic formation) and not only used as a tool. Four lines of inquiry follow. First, *archival and historical*: how digitisation and AI reconfigure African pasts, building on evidence of digital bias in colonial-era catalogues (Błoch et al., 2025). Second, *categorical ethnography*: how specific African concepts of personhood, kinship, property and privacy fare when encoded in data systems, extending studies of privacy in Ghana (Kadiri & Boamah, 2025). Third, *reception*: how African audiences decode, negotiate or resist AI, following studies of AI news presenters (Ndlovu, 2024) and encoding/decoding (Yin, 2025). Fourth, *political economy*: who owns, finances and governs African AI, including South–South relations (Tse et al., 2025; Soulé, 2025) and the role of development framings (de Silva, 2025; Mannuru et al., 2025).

4.2 DISCUSSION

The framework reframes the debate about decolonising AI. Much of the policy discussion treats the problem as one of inclusion: Africa is missing from data, so Africa should be added. The evidence reviewed here supports that diagnosis at the data layer but shows that it is incomplete. Consistent with Lassen et al. (2025), exclusion is self-reinforcing through deployment; consistent with Clausen et al. (2025), representation at a distance reshapes what is represented. The framework explains why: data are always collected, labelled and evaluated through categories, and those categories are set by institutions.

The findings extend decolonial theory in two ways. First, following Fosu (2025), they locate African agency inside the structure rather than only outside it. Local intermediaries co-produce coloniality (Effoduh, 2025), but African governments also exercise agency through diversified partnerships (Soulé, 2025) and through regional instruments that prioritise regulatory sovereignty (Vásquez Callo-Müller & Sucker, 2026). Second, the findings specify what representation requires. The Ubuntu literature (Mokoena, 2024; Ferlito et al., 2024; Sule, 2026) is often presented as an alternative ethics; the framework suggests it is also evidence that the categorical layer is culturally specific and therefore open to contestation.

The sovereignty–openness tension deserves particular attention. Indigenous data sovereignty scholarship (Prehn et al., 2026) and African data-governance research both show that extraction is real. Yet African research depends on data sharing, and researchers report that legal gaps and mistrust already inhibit it (Chabilall et al., 2024; Cengiz et al., 2024). The framework suggests that sovereignty and

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openness are compatible when sovereignty means *control over terms* rather than *closure*: federated analysis with local control (Kiragga et al., 2025), culturally grounded consent and trust (Ekusai-Sebatta et al., 2026), and governance frameworks that are demonstrably enforceable rather than declared (Raman & Nedungadi, 2026). Without such capacity, sovereignty risks becoming a product sold back to those who claim it (Grohmann & Barbosa, 2026).

For policy, the framework cautions against treating decolonisation as a dataset problem. Regulation remains fragmented (Townsend et al., 2023), and public administrations adopting AI face questions of accountability and inclusive decision-making (Plantinga, 2024). Policy should therefore address all three layers: funding African data creation (data layer), requiring community participation in problem definition and evaluation (categorical layer), and building public and community ownership of infrastructure and governance (institutional layer). Decoloniality impact assessment (Eke et al., 2026) offers a practical vehicle.

The paper has limitations. It is conceptual, and its propositions await empirical testing. The sample was restricted to verified 2023–2026 journal articles, which excludes foundational decolonial works, conference-based NLP research and grey literature; access constraints on some publisher platforms meant that some relevant articles could not be verified and were excluded. Evidence on the categorical layer remains thinner than on the data and institutional layers, and much of it comes from South Africa, Ghana and Kenya rather than from francophone, lusophone or North African contexts. Future research should test the propositions through comparative audits of systems trained with and without community-defined categories, ethnographies of African AI development, and longitudinal studies of data-sharing governance.

5. CONCLUSION AND RECOMMENDATION

This paper has argued that coloniality in AI operates at three layers: data, categories and institutions. Representation-only remedies act mainly on the first and therefore risk producing inclusion without representation, in which African data improve system performance while African concepts are overwritten and African institutions remain peripheral. Representation requires that African communities shape the categories through which their knowledge is processed and hold power in the institutions that build and govern AI. Data sovereignty is essential to that goal, but it serves African research best when exercised as governed sharing rather than closure.

Six recommendations follow. **First**, AI developers and funders working in Africa should involve affected communities and knowledge custodians in defining problems, labels and evaluation metrics, not only in supplying data. **Second**, African governments and the African Union should adopt decoloniality impact assessment as part of AI procurement and regulation, examining who defines problems, whose knowledge counts and who benefits. **Third**, data-governance regimes should favour governed sharing (standard data-sharing agreements, culturally grounded consent, federated analysis and local control) over both unrestricted extraction and blanket closure. **Fourth**, sovereignty strategies should prioritise demonstrable capacity to inspect, run and contest AI systems over branded "sovereign" services. **Fifth**, research ethics committees and data regulators should be trained and resourced to review data-intensive and AI research. **Sixth**, African universities and funders should support African studies research that treats AI as an object of study, especially archival, categorical, reception and political-economy research.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The paper makes four contributions. **Conceptually**, it distinguishes three layers of coloniality in AI (data, categorical and institutional) and introduces the distinction between *inclusion* and *representation*, naming the outcome of representation-only remedies as inclusion without representation. **Theoretically**, it integrates decolonial theory beyond the West–Africa binary, epistemic injustice, encoding/decoding, Ubuntu ethics and the politics of locationality into a single framework, and treats the sovereignty–openness tension as a structural feature of decolonising AI rather than a policy detail. **Empirically**, it consolidates recent verified evidence from language technology, media, health, finance, public administration and research governance into an evidence map and a set of operational indicators. **For African studies and policy**, it proposes a research agenda that treats AI as an object of study

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and identifies practical instruments (community-defined categories, decoloniality impact assessment, governed data sharing and demonstrable sovereignty) through which AI can represent rather than overwrite African knowledge.

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