

Original articles

Cloud, control and diagnostic sovereignty: the political economy of AI-enabled health diagnostics in Africa

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Background

The rapid adoption of artificial intelligence (AI) in African healthcare presents both transformative opportunities and structural risks. While AI-enabled diagnostic technologies may expand clinical capacity and improve service delivery, their deployment also raises questions of data sovereignty, infrastructural dependency, regulatory auditability, and unequal value capture.

Methods

This exploratory multi-case analysis examines four African health technology firms: Helium Health, Ubenwa, Neural Labs Africa, and Envisionit Deep AI. The study draws on publicly available secondary sources published between 2017 and 2025, comprising 26 peer-reviewed or academic sources, 6 policy and regulatory documents, and 4 firm-level sources. A thematic analysis was conducted through a political-economy framework using deductive and inductive coding.

Results

Publicly available documentation suggests three recurring structural patterns. First, the selected firms rely on AWS or Google Cloud for key infrastructure functions, creating potential limits on domestic regulatory oversight of diagnostic data pipelines and model updates. Second, the absence of publicly documented locally governed datasets and systematic local retraining points to data sovereignty and clinical validation gaps. Third, fragmented data protection regimes across Nigeria, Kenya, and South Africa create governance asymmetry that may constrain the cross-border data pooling needed for African AI model development.

Conclusions

Diagnostic equity in African health AI requires governance over data, infrastructure, models, and validation systems. The study proposes tiered data sovereignty frameworks, regionally coordinated health data trusts, and staged AI validation sandboxes as practical pathways for reducing dependency while preserving innovation capacity. Findings are exploratory and should be interpreted in light of reliance on publicly available evidence.

When an AI system supports a diagnosis in Lagos, Nairobi, Accra, or Johannesburg, who controls the data, who validates the algorithm, and who is accountable when the system fails? This question is increasingly urgent as African health systems adopt AI-enabled diagnostic technologies to respond to rising disease burdens, workforce shortages, and unequal access to specialist care.

In this article, AI-enabled diagnostic technologies are defined as digital tools that use machine learning or related artificial intelligence techniques to analyse clinical, imaging, laboratory, audio, genomic, electronic medical record, or patient-reported symptom data in order to support, aug-

ment, or partially automate diagnostic decision-making. These systems may be embedded in telemedicine platforms, electronic medical records, radiology workflows, point-of-care testing, or mobile health applications. Their outputs can include risk scores, triage recommendations, disease classifications, abnormality detection, or suggested clinical pathways.

Over the past decade, debates on AI diagnostics in Africa have evolved from optimism about technological leapfrogging to more critical reflection on power, dependency, and governance. Early discussions emphasised AI as a response to shortages of health professionals, weak referral systems,

and limited diagnostic infrastructure.^{1,2} More recent scholarship has questioned whether these technologies can reproduce existing inequalities when they are trained on non-African datasets, hosted on foreign cloud infrastructure, governed through opaque proprietary systems, and deployed in health systems with limited regulatory capacity.^{3–8} The question is therefore no longer only whether AI can improve diagnostic performance, but whether African patients, clinicians, regulators, and innovators can govern the systems that increasingly shape diagnostic decisions.

The problem is not abstract. Patients in under-resourced settings may suffer from misclassification, delayed referral, inappropriate treatment pathways, or diagnostic tools that perform poorly for local epidemiological profiles. Frontline clinicians may become dependent on decision-support systems whose assumptions, limitations, and update cycles are not transparent. Public regulators may be unable to audit algorithms or enforce accountability when data storage, model training, and model updates occur outside their jurisdiction. Local innovators may also face dependency on foreign platforms and training data, while African health systems risk losing economic value from data generated by their own populations.

The social and economic costs are significant. Clinically, poorly validated AI diagnostics can undermine patient safety and trust. Economically, dependence on externally governed cloud infrastructure may lock ministries, insurers, and providers into recurring costs while limiting domestic AI capacity building. Socially, weak data governance may intensify data extraction, where African health data improve externally controlled models without equivalent reinvestment in local infrastructure, skills, or public health priorities. These dynamics could create a new digital divide in which AI expands access for some while deepening structural dependency for others.

This paper examines the political economy of AI-enabled diagnostic innovation in Africa through a multi-case analysis of Helium Health, Ubenwa, Neural Labs Africa, and Envisionit Deep AI. It asks how cloud infrastructure choices, cross-border data flows, and fragmented regulatory regimes shape diagnostic sovereignty. The study addresses two gaps in the literature: first, limited analysis of data sovereignty as a foundation for diagnostic equity; and second, limited attention to how global market forces, platform power, and geopolitical interests structure control over AI diagnostic infrastructures. The significance of the study lies in reframing AI diagnostics as a governance question: equitable AI in African health systems requires not only ethical algorithms, but public and regional capacity to govern data, infrastructure, models, and validation systems.

THEORETICAL FRAMEWORK: POLITICAL ECONOMY OF AI-ENABLED DIAGNOSTICS IN AFRICA

The political economy of technology examines how political, economic, and social forces structure the development, diffusion, ownership, and control of technological systems.^{9–11} Applied to AI-enabled diagnostics, this perspective shifts attention from model accuracy alone to the

institutional and infrastructural conditions under which diagnostic systems are built, deployed, governed, and monetised.

Three dimensions are particularly relevant. First, state power and geopolitical competition shape where digital infrastructures are built, who finances them, and whose strategic priorities they serve. Cloud services, data centres, and communication networks function as geopolitical assets that can extend influence and structure dependency.^{12–14} Second, corporate concentration allows a small number of technology firms to control layers of the AI value chain, including cloud infrastructure, data standards, computational resources, and platform interfaces.^{5,7,10,15} Third, political economy perspectives highlight how technological systems reproduce inequalities in access and value capture, especially where Global South actors supply data and markets while Global North actors retain control over infrastructure, intellectual property, and monetisation pathways.^{5,7,16,17}

The analytical pathway used in this study is therefore: global platform control over cloud and compute infrastructure shapes data location and model governance; data location and model governance influence regulatory auditability and local retraining capacity; and auditability and retraining capacity affect diagnostic equity, accountability, and sovereignty. This framework guides the coding of four dimensions across cases: cloud dependency, data ownership and location, model validation and retraining, and regulatory exposure.

METHODS

This study uses an exploratory multi-case analysis supported by a targeted review of academic and grey literature. It applies a political-economy framework to publicly available secondary data on four African health AI firms. Because no primary data were collected and no internal firm documentation was accessed, the findings should be interpreted as evidence of publicly observable patterns rather than definitive verification of internal infrastructure configurations or compliance practices.

COUNTRY AND CASE SELECTION

Nigeria, Kenya, and South Africa were selected because they represent active digital health environments with variation in market size, regulatory capacity, and digital infrastructure. Four firms—Helium Health, Ubenwa, Neural Labs Africa, and Envisionit Deep AI—were purposively selected¹⁸ based on: (i) maturity and visibility through active deployment or advanced pilots; (ii) technological variety, including electronic medical records, AI-supported triage, sound-based diagnostics, and medical imaging; and (iii) geographic and regulatory diversity across the three countries. This approach prioritises analytical relevance over representativeness.

DATA SOURCES AND SEARCH STRATEGY

The final dataset comprised 36 documents: 26 academic sources, 6 policy or regulatory documents, and 4 firm-level sources. Documents were identified through searches of Google Scholar, PubMed, and Scopus using terms including ‘artificial intelligence AND Africa AND health’, ‘health AI AND data sovereignty’, ‘digital health AND cloud infrastructure AND Africa’, and ‘AI governance AND Global South’. Grey literature and policy documents were retrieved from the African Union, national data protection authorities, the World Health Organization, and relevant official websites. Firm-level sources were retrieved from company websites and publicly available product or technical descriptions. Searches were conducted between November 2025 and January 2026. Documents were included if they were published between 2017 and 2025, addressed AI, digital health, data governance, cloud infrastructure, or relevant political-economic dynamics, and were available in English. Documents were excluded if they were purely clinical or technical without relevance to governance, data infrastructure, or political economy.

CODING AND ANALYSIS

Thematic coding combined deductive and inductive procedures. Deductive codes were developed from the political-economy framework and included data ownership, cloud dependence, regulatory jurisdiction, cross-border data transfer, model validation, model retraining, value capture, and infrastructural control. Inductive coding identified additional themes emerging from the documents, including infrastructural lock-in, externalised regulatory authority, scalability-sovereignty trade-offs, and governance asymmetry. Each case was analysed along comparable dimensions: cloud provider, infrastructure function, data location or movement, model validation and retraining evidence, and regulatory exposure.

EVIDENCE STANDARDS

A claim was retained as a finding only when it was supported by at least one firm-level source and contextualised by policy, regulatory, or academic sources. Where public documentation did not provide evidence of a practice, the manuscript uses cautious language such as ‘no publicly available evidence was identified’ rather than treating absence of documentation as proof that the practice does not exist. Claims about AWS, Google Cloud, offshore processing, and model retraining therefore refer to publicly observable evidence, not independently audited infrastructure records. This distinction is important because firm websites, public product descriptions, and regulatory documents cannot fully reveal contractual arrangements, internal compliance procedures, or technical architecture.

RESULTS

Analysis of the four firms—Helium Health, Ubenwa, Neural Labs Africa, and Envisionit Deep AI—identified three recur-

ring structural patterns: infrastructural lock-in, data sovereignty deficits, and governance asymmetry. These patterns are based on publicly available sources and should be read as indicative evidence rather than independently audited infrastructure findings.

INFRASTRUCTURAL LOCK-IN

Across the four cases, publicly available documentation indicates reliance on foreign hyperscale cloud providers for key infrastructure functions. Helium Health is associated with AWS and Google Cloud Platform for clinical and financial services. Ubenwa is associated with Google Cloud-based pipelines for audio processing and model training. Neural Labs Africa and Envisionit Deep AI are associated with AWS for imaging platform deployment and diagnostic inference. These observations were coded under cloud dependence and regulatory jurisdiction.

The result is not that the firms necessarily lack agency or that foreign cloud services are inherently harmful. Rather, the pattern suggests that essential layers of AI diagnostic functionality—storage, compute, training, inference, and updates—may be located outside domestic regulatory reach. This creates a potential lock-in problem: local service delivery depends on external infrastructure, and regulators may not have direct access to the systems needed to audit clinical performance or model changes.

DATA SOVEREIGNTY DEFICITS AND CLINICAL RELEVANCE

Publicly available sources did not identify systematic local retraining or locally governed datasets across the four cases. This does not prove that such practices are absent; rather, it indicates a transparency gap. In AI diagnostics, the absence of publicly documented local validation is consequential because diagnostic performance depends on whether models are tested against the demographic, epidemiological, linguistic, and clinical characteristics of the populations in which they are deployed.

Regulatory documents show that cross-border health data flows are subject to different requirements across Nigeria, Kenya, and South Africa. Nigeria’s NDPR framework permits transfers subject to safeguards, Kenya’s Data Protection Regulations require appropriate safeguards and regulatory processes for cross-border transfers, and South Africa’s POPIA Section 72 requires that transferred personal information receive adequate protection. These differences create compliance complexity for firms operating across borders and may constrain the pooling of African clinical datasets needed for locally relevant model development.

GOVERNANCE ASYMMETRY

The four cases show a recurring asymmetry between local service delivery and external infrastructure control. Clinical triage, hospital management, neonatal screening, and radiology support are delivered within African health systems, but core infrastructure functions may be hosted through

Table 1. Transparency matrix of the 36 coded documents

No.	Document/source	Type	Coding role
1	Etori et al. (2023), What we know so far: AI in African healthcare	Academic/preprint	AI health context in Africa
2	Korom et al. (2025), AI-based clinical decision support for primary care	Academic/preprint	Clinical decision-support context
3	Arakpogun et al. (2021), Artificial intelligence in Africa	Academic chapter	AI opportunities and structural challenges
4	De Freitas (2025), Digital sovereignty and data colonialism	Policy paper	Digital sovereignty and Global South context
5	Couldry and Mejias (2019), The Costs of Connection	Academic book	Data colonialism and value extraction
6	Martin (2021), Geopolitics and digital sovereignty	Academic chapter	Digital sovereignty and geopolitical framing
7	Birhane (2020), Algorithmic colonization of Africa	Peer-reviewed article	Algorithmic colonialism and African AI governance
8	Gwagwa et al. (2022), Ubuntu and global AI inclusion discourse	Peer-reviewed article	African-centred AI ethics
9	Bijker et al. (1987), Social Construction of Technological Systems	Academic book	Technology and society framework
10	Srnicek (2017), Platform Capitalism	Academic book	Platform concentration and infrastructural control
11	Farrell and Newman (2019), Weaponized interdependence	Peer-reviewed article	Geopolitical dependency in networked infrastructure
12	Herr (2020), Four myths about the cloud	Policy report	Cloud geopolitics
13	World Economic Forum (2025), AI geopolitics and data centres	Policy commentary	Data centres and AI geopolitical rivalry
14	Crawford (2021), Atlas of AI	Academic book	Material and political costs of AI
15	Mohamed et al. (2020), Decolonial AI	Peer-reviewed article	Decolonial AI theory
16	Zuboff (2019), Age of Surveillance Capitalism	Academic book	Surveillance capitalism and data value capture
17	Andreoni and Roberts (2022), Governing digital platform power	Peer-reviewed article	Digital platform power and industrial policy
18	African Union/Pan-African Parliament (2025), Data sovereignty and ethical AI	Policy statement	Continental data sovereignty policy context
19	Alaran et al. (2025), AI in African health space	Peer-reviewed article	Challenges and opportunities in African health AI
20	The Future Society (2022), AI in Healthcare in Africa	Policy report	African AI health ecosystem
21	WHO/ITU AI for Health programme	Policy/technical source	AI for health governance and standards context
22	Kwet (2019), Digital colonialism	Academic/preprint	Digital colonialism and Global South dependency
23	Kasy (2024), Political economy of AI	Working paper	Democratic control of predictive systems
24	Andigema et al. (2025), AI in African healthcare	Preprint	Structural challenges and innovation
25	Moleka (2023), Diagnostic sovereignty in African health systems	Grey/academic source	Diagnostic sovereignty framing
26	Monahan (2008), Surveillance and inequality	Peer-reviewed article	Surveillance and inequality
27	Tajik et al. (2024), Purposive sampling	Peer-reviewed article	Case-selection justification
28	Nigeria NDPR Implementation Framework (2021)	Regulatory document	Nigeria cross-border data and compliance context
29	Kenya Data Protection (General) Regulations (2021)	Regulatory document	Kenya cross-border data transfer rules
30	South Africa POPIA, Section 72	Regulatory document	South Africa transfer of personal information
31	African Union Data Policy Framework (2022)	Policy framework	Regional data governance and harmonisation
32	African Union Continental AI Strategy (2024)	Policy strategy	Africa-centred AI governance context
33	Helium Health website/about/product materials	Firm-level source	Case evidence: EMR, telemedicine, cloud-linked services
34	Ubenwa website/about/research materials	Firm-level source	Case evidence: sound-based neonatal AI diagnostics
35	Neural Labs Africa website/resources	Firm-level source	Case evidence: medical imaging AI and platform deployment
36	Envisionit Deep AI website/platform materials	Firm-level source	Case evidence: radiology AI and platform deployment

AWS or Google Cloud. This separates the site of clinical impact from the site of technical control.

This asymmetry matters because diagnostic sovereignty depends on more than data ownership. It requires the ca-

Table 2. Publicly observable infrastructure evidence across cases

Firm	Primary setting	Publicly reported cloud provider	Reported infrastructure function	Governance implication
Helium Health	Nigeria, Ghana, Kenya, Uganda, Liberia	AWS and Google Cloud Platform reported in public documentation	Storage, computation, EMR, telemedicine, billing and health-financing functions	Cross-border processing may trigger NDPR and related data-transfer safeguards; public evidence of local model retraining was not identified.
Ubenwa	Nigeria/Canada-linked research collaborations	Google Cloud Platform reported in public and research-facing materials	Audio data processing, AI inference, dataset storage and acoustic model training	Processing of Nigerian neonatal audio data outside Nigeria may require safeguards under NDPR; public evidence of locally governed Nigerian training datasets was not identified.
Neural Labs Africa	Kenya	AWS reported in public resources	Medical imaging AI platform deployment and scalability	Offshore storage or processing may require appropriate safeguards under Kenya's Data Protection Act and General Regulations; public evidence of local audit access was not identified.
Envisionit Deep AI	South Africa	AWS reported in public platform materials	Radiology image analysis, algorithmic inference and cloud-based deployment	Offshore processing may trigger POPIA Section 72 protections for transfers outside South Africa; public evidence of direct regulator access to model updates was not identified.

capacity to inspect datasets, test model performance, audit updates, govern cross-border transfers, and require corrective action when models underperform. Across the four cases, no publicly available evidence was identified showing direct regulatory access to externally hosted model training or update environments.

DISCUSSION

The three patterns identified—infrastructural lock-in, data sovereignty deficits, and governance asymmetry—point to a form of structural dependency that may limit the capacity of African health systems to govern diagnostic AI in the public interest. The issue is not merely that diagnostic data may cross borders. Rather, the concern is that data, compute, model training, inference, validation, and update systems can be distributed across jurisdictions in ways that make domestic regulatory authority difficult to exercise.

The reliance of the selected firms on AWS or Google Cloud is consistent with broader literature on hyperscaler dominance in Global South technology ecosystems.^{5,7,10,19} Platform capitalism concentrates control over algorithms, standards, data infrastructures, and computational resources within a small number of global firms. In African health AI, this can position local innovators as deployers of externally governed infrastructures rather than full governors of the diagnostic systems they build.

The policy challenge is therefore layered. Data localisation alone is insufficient if model training, audit logs, inference engines, and update mechanisms remain externally governed. Equally, prohibiting foreign cloud infrastructure outright could restrict innovation and scalability in resource-limited settings. A more practical approach is

staged sovereignty: retaining access to global cloud capacity while progressively building local and regional governance over sensitive data, validation, and audit functions.

OPERATIONALISING DIAGNOSTIC SOVEREIGNTY

These pathways are complementary. Tiered data sovereignty defines what must be governed locally or regionally; data trusts provide institutional mechanisms for responsible dataset pooling; validation sandboxes create pathways for safe and adaptive regulation; audit infrastructure gives regulators visibility over models and updates; and procurement rules convert public spending into long-term domestic capacity. Together, they move the debate from abstract sovereignty to implementable governance design.

LIMITATIONS

Several limitations must be acknowledged. First, this study relies exclusively on publicly available secondary data, including firm websites, published academic literature, public policy documents, and accessible regulatory instruments. No interviews were conducted with firm representatives, regulators, clinicians, patients, or cloud providers. The study therefore cannot independently verify internal infrastructure configurations, contractual arrangements, retraining practices, or compliance procedures.

Second, the purposive selection of four firms from three countries prioritises analytical relevance over representativeness. Firms with strong public visibility and links to foreign cloud infrastructure may be overrepresented relative to smaller, community-based, locally financed, or public-sector initiatives. The findings should therefore not be generalised to all African health AI projects.

Table 3. Policy pathway for governing AI-enabled diagnostics in Africa

Policy instrument	Lead institutions	Operational steps	Time horizon	Expected contribution
Tiered data sovereignty framework	National data protection authorities, ministries of health, health facility regulators	Classify data into tiers: raw identifiable clinical data, pseudonymised clinical datasets, metadata, model outputs, audit logs, and model weights. Require local or regional hosting for the most sensitive tiers while allowing controlled cross-border processing for lower-risk tiers.	0-24 months	Clear rules on what must remain under domestic or regional jurisdiction.
Regional health data trusts	African Union, Africa CDC, regional economic communities, national regulators, public universities	Create governed institutions for pooling de-identified clinical datasets across countries. Include patient/community representation, ethics oversight, access committees, benefit-sharing rules, and audit requirements for firms using pooled datasets.	1-5 years	Larger, more representative African datasets for model training and validation.
Tiered validation sandboxes	National regulators, medical device agencies, teaching hospitals, professional councils	Test AI diagnostic tools in staged environments: technical validation, retrospective clinical validation, prospective supervised deployment, and post-market monitoring. Require reporting on accuracy, bias, safety, explainability, cybersecurity, and population-specific performance.	0-36 months	Faster innovation with patient-safety safeguards and regulatory learning.
Public audit infrastructure	Ministries of health, data protection authorities, regional centres of excellence	Require firms to provide audit logs, model cards, dataset documentation, update histories, and incident reporting. Build regulator capacity to inspect cloud-hosted systems through contractual audit rights and secure interfaces.	1-4 years	Improved regulatory visibility over externally hosted models and updates.
Local capacity and procurement rules	Governments, donors, development finance institutions, universities	Tie public procurement and donor-funded AI projects to local skills transfer, local validation, data-access provisions, and domestic or regional compute partnerships.	1-5 years	Reduced long-term dependency and stronger African AI innovation ecosystems.

Third, the political-economy framework foregrounds structural constraints and power asymmetries. This lens may understate firm-level innovation, adaptive strategies, and local governance practices that are not visible in public documents. Future research should combine technical audits, interviews, regulatory analysis, and patient-centred evaluation to test the patterns identified here.

CONCLUSIONS

AI-enabled diagnostics are often presented as tools for closing gaps in access to care. This article argues that they may also create a new digital divide if African health systems lack control over the data, infrastructure, models, and validation systems that shape diagnostic decisions. The central contribution of the study is to show that diagnostic sovereignty is not reducible to data ownership or data localisation. It requires the capacity to govern the full diagnostic AI pipeline: clinical data collection, storage, cross-border transfer, model training, inference, updating, validation, audit, and accountability.

The multi-case analysis identified three publicly observable patterns across four African health technology firms: infrastructural lock-in, data sovereignty deficits, and governance asymmetry. These findings are exploratory, but they indicate that local clinical deployment can coexist with external control over essential technical infrastructure. Where this occurs, the benefits of AI diagnostics may be unevenly distributed, while patients, clinicians, regulators, and public health systems bear the risks of weak validation, limited auditability, and dependency on foreign platforms.

Preventing this outcome requires a shift from narrow AI ethics to political-economic governance. African governments and regional institutions should develop tiered data sovereignty frameworks, regional health data trusts, validation sandboxes, public audit infrastructure, and procurement rules that build domestic and regional capacity. The goal is not technological isolation, but accountable interdependence: African health systems should be able to use global AI capabilities while retaining meaningful authority over the diagnostic data, infrastructures, models, and validation processes that affect their populations.

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AUTHORSHIP CONTRIBUTIONS

Kopati Gbali Carl Adams and Okechukwu Ignatius Eze conceived the study. Kopati Gbali Carl Adams wrote the first draft with contributions from Francisca Arboh. Okechukwu Ignatius Eze revised the draft and checked for intellectual content. All authors approved the manuscript as submitted.

COMPETING INTERESTS

None declared.

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REFERENCES

1. Etori N, Temesgen E, Gini M. What we know so far: artificial intelligence in African healthcare. *arXiv preprint*. Published online 2023. <https://arxiv.org/abs/2305.18302>
2. Korom R, Kiptinness S, Adan N, Said K, Ithuli C, Rotich O, et al. AI-based clinical decision support for primary care: a real-world study. *arXiv preprint*. Published online 2025. <https://arxiv.org/abs/2507.16947>
3. Arakpogun EO, Elsahn Z, Olan F, Elsahn F. Artificial intelligence in Africa: challenges and opportunities. In: *The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success*. Springer; 2021:375-388. doi:[10.1007/978-3-030-62796-6_22](https://doi.org/10.1007/978-3-030-62796-6_22)
4. De Freitas MV. *Digital Sovereignty and Data Colonialism: Shaping a Just Digital Order for the Global South*. Policy Center for the New South; 2025.
5. Couldry N, Mejias UA. *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism*. Stanford University Press; 2019. doi:[10.1515/9781503609754](https://doi.org/10.1515/9781503609754)
6. Martin C. Geopolitics and digital sovereignty. In: Werthner H, Prem E, Lee EA, Ghezzi C, eds. *Perspectives on Digital Humanism*. Springer; 2021:227-231. doi:[10.1007/978-3-030-86144-5_30](https://doi.org/10.1007/978-3-030-86144-5_30)
7. Birhane A. Algorithmic colonization of Africa. *SCRIPTed*. 2020;17(2):389-409. doi:[10.2966/scrip.170220.389](https://doi.org/10.2966/scrip.170220.389)
8. Gwagwa A, Kazim E, Hilliard A. The role of the African value of Ubuntu in global AI inclusion discourse: a normative ethics perspective. *Patterns*. 2022;3(4):100462. doi:[10.1016/j.patter.2022.100462](https://doi.org/10.1016/j.patter.2022.100462)
9. Bijker WE, Hughes TP, Pinch TJ, eds. *The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology*. MIT Press; 1987.
10. Srnicek N. *Platform Capitalism*. Polity Press; 2017.
11. Monahan T. Surveillance and inequality. *Surveillance & Society*. 2008;5(3):217-226. doi:[10.24908/ss.v5i3.3421](https://doi.org/10.24908/ss.v5i3.3421)
12. Farrell H, Newman AL. Weaponized interdependence: how global economic networks shape state coercion. *International Security*. 2019;44(1):42-79. doi:[10.1162/isec_a_00351](https://doi.org/10.1162/isec_a_00351)
13. Herr T. *Four Myths about the Cloud: The Geopolitics of Cloud Computing*. Atlantic Council, Scowcroft Center for Strategy and Security; 2020.
14. World Economic Forum. AI geopolitics and data centres in the age of technological rivalry. World Economic Forum. 2025. Accessed 2025. <https://www.weforum.org/stories/2025/07/ai-geopolitics-data-centres-technological-rivalry/>
15. Crawford K. *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. Yale University Press; 2021. doi:[10.12987/9780300252392](https://doi.org/10.12987/9780300252392)
16. Mohamed S, Png MT, Isaac W. Decolonial AI: decolonial theory as sociotechnical foresight in artificial intelligence. *Philosophy & Technology*. 2020;33(4):659-684. doi:[10.1007/s13347-020-00405-8](https://doi.org/10.1007/s13347-020-00405-8)
17. Zuboff S. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. PublicAffairs; 2019.
18. Tajik O, Golzar J, Noor S. Purposive sampling. *International Journal of Education and Language Studies*. 2024;2(2).
19. Andreoni A, Roberts S. Governing digital platform power for industrial development: towards an entrepreneurial-regulatory state. *Cambridge Journal of Economics*. 2022;46(6):1431-1454. doi:[10.1093/cje/beac055](https://doi.org/10.1093/cje/beac055)