IIAR JOURNALS

Innovating Knowledge. Advancing Research.

IIAR Journal of Social Sciences and African Studies

Vol 1, No 1, 2026

Computational Social Science and African Realities: A Methodological and Theoretical Critique of Big Data, Machine Learning and the Measurement of African Societies

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ABSTRACT

Social scientists increasingly measure African societies through data that Africans did not produce for that purpose: satellite imagery, night-time lights, mobile-phone and platform data, social-media text, conflict event records and, most recently, large language models, processed by machine learning into estimates of poverty, population, inequality, conflict and opinion where surveys and censuses are missing or late. Evaluations of these methods focus mainly on predictive accuracy, and the problems they raise are discussed in separate literatures that seldom engage interpretive African social science. This paper offers a methodological and theoretical critique. Its objectives are to integrate recent evidence into a single framework, derive propositions on the conditions of validity and the policy consequences of computational measurement, clarify the relationship between computational and interpretive research, and propose standards for responsible use. The study is an integrative, theory-building review. The population was peer-reviewed journal articles published between 2023 and 2026; a purposive sample of 41 articles was retained from 73 fully screened records after verification against publisher records and screening for retractions, corrections and expressions of concern. Findings were coded against three provisional problems, compared across data sources and synthesised abductively. The analysis yields a coverage–validity–reflexivity framework. Coverage gaps are structured, falling on poorer, rural, less educated and female populations; construct validity weakens as the distance between signal and concept grows; and measurement used for policy changes what it measures. Computational methods therefore ease data scarcity while introducing biases harder to see than those of the surveys they supplement. Seven propositions address structured coverage, inherited labels, proxy distance, invisible bias, reflexivity, measurement authority and complementarity with interpretive research, illustrated with Nigerian cases. The paper recommends coverage statements, disaggregated local validation with reported uncertainty, explicit construct-validity arguments, reflexivity assessments and appeal mechanisms before computational measures are used for allocation, partnership with national statistical offices, African research leadership, and caution in substituting language-model outputs for African respondents.

Keywords: computational social science; big data; machine learning; measurement; data gaps

1. INTRODUCTION

African social science has long worked under conditions of data scarcity. Censuses are irregular and contested, household surveys are expensive and infrequent, and the statistical systems that produce official numbers are unevenly resourced. In the 2020 census round, most countries still collected data directly from respondents using traditional methods (Dindi & Stiegler, 2025), and measures of national statistical capacity continue to show wide gaps between countries (Dang et al., 2024). Into this gap has moved a new apparatus of measurement. Satellite imagery, night-time lights, mobile-phone records, social-media text and, most recently, large language models (LLMs) are processed by machine learning (ML) into estimates of poverty, population, inequality, conflict and opinion for places that surveys and censuses do not reach or reach too late.

The promise is considerable. Convolutional neural networks trained on satellite images can rank the wealth of survey clusters in Tanzania more accurately than human experts (Sarmadi et al., 2024); open geospatial data can map deprived urban areas in Accra, Lagos and Nairobi with high accuracy (Owusu et al., 2023); and gridded night-light data can be used to estimate inequality for each of Nigeria's 774 local government areas (Maduako et al., 2025). For governments, donors and researchers, such methods appear to dissolve the scarcity that has constrained African social science for decades.

This paper argues that the promise comes with a cost that is easy to overlook. Computational methods do ease data scarcity, but they also introduce biases that are harder to see than those of the surveys they supplement or replace. Errors are spatially structured rather than random (Ru et al., 2026); they depend on choices of source and coding that users rarely examine (Raleigh et al., 2023); and they are embedded in model pipelines whose validation is often thin (Park & Montgomery, 2026). When such measures are used to allocate social assistance, errors become exclusions (Dietrich et al., 2024; Kemal, 2026). And when digital sources are privately owned, authority over the counting of African populations shifts away from public statistical systems (Darin, 2025).

The literature that documents these issues is scattered across remote sensing, development economics, political methodology, critical data studies, law and African studies, and it rarely speaks to the interpretive traditions of African social science. The paper therefore offers a methodological and theoretical critique organised around three problems: *coverage* (who is in the data), *construct validity* (whether the proxy measures the concept), and *reflexivity* (whether the measurement changes what it measures). Its objectives are (i) to synthesise recent peer-reviewed evidence on computational measurement of African societies into a single framework; (ii) to derive propositions about the conditions under which computational measures are valid for African contexts and about the consequences when policy is made on their basis; (iii) to clarify the relationship between computational and interpretive African social science; and (iv) to propose standards for the responsible use of big data and ML in research on African societies. The guiding questions are: Whose realities do computational measures capture? What do they actually measure? And what happens to African societies when they are measured this way?

2. LITERATURE REVIEW

2.1 CONCEPTUAL REVIEW

2.1.1 Computational social science and big data

Computational social science refers here to the measurement and analysis of social phenomena using large, often naturally occurring digital data and algorithmic methods, especially ML. *Big data* refers to data that were not produced for the research purpose to which they are put: imagery collected by satellites, records generated by telecommunications networks, text posted on platforms, and administrative or biometric registries. Public discourse has framed such data through imaginaries of social renewal, commercial revival and surveillance; a study of press coverage in Germany, South Africa and the United States found positive framings largely prevailing despite major data scandals (Knorr & Pentzold, 2025).

2.1.2 Measurement, proxies and validity

Measurement is the assignment of values to social phenomena according to rules; a *proxy* is an

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observable signal used in place of a concept that cannot be observed directly. Night-time light stands in for economic activity, roof materials for household wealth, tweets for public opinion and reported events for violence. *Construct validity* is the degree to which a proxy captures the concept it is meant to measure. Recent methodological work shows that validation of ML-based measures is often incomplete: a review of supervised text-analysis studies in two leading political science journals found that few validated their labels or final measures (Park & Montgomery, 2026).

2.1.3 Coverage, reflexivity and data sovereignty

Coverage concerns the relationship between those represented in a data source and the population about which inferences are made. *Reflexivity* refers to the capacity of measurement to change what it measures: through people's responses to being measured, through policies built on the measures, or through the political control of data. *Data sovereignty* refers to the authority of states and communities over data about them. Critical scholarship frames the global data economy as "uneven datafication," in which value is extracted from peripheral regions through territorialisation, dispossession and unequal exchange (Akbari, 2026), and African AI governance as shaped by dependence on foreign technology (Okocha & Zoho, 2026).

2.2 THEORETICAL REVIEW

Four theoretical lenses from the recent literature inform the critique.

Measurement theory and the validity framework. The classical distinction between construct, statistical, external and internal validity has been adapted to supervised ML (Park & Montgomery, 2026). Applied to computational social science in Africa, it implies that predictive accuracy on held-out survey data, the usual benchmark, is not sufficient evidence that a model measures welfare, opinion or violence across places and times.

Critical data studies and political economy. Critical data studies examine data as products of power. The uneven-datafication framework draws on decolonial, dependency and uneven-development scholarship to explain how data-driven capitalism reproduces global inequality (Akbari, 2026). Darin (2025) applies a similar logic to demography, arguing that satellite imagery, mobile-phone data and social media have shifted population counting from a state-led public good towards a privately controlled asset. These lenses explain why coverage and ownership are political, not merely technical.

Science and technology studies and performativity. Work in science and technology studies holds that measurement and prediction do not simply describe the world but help to make it. Lazaro and Rizzi (2023) argue that coupling AI with governance makes the future appear knowable in the present and thereby steers present decisions under logics of precaution, pre-emption and preparedness. This lens underpins the reflexivity problem.

Critical and decolonial data science. Van Geene et al. (2026) propose a critical data science framework built on decoloniality, intersectionality, transdisciplinarity and reflexivity, which prompts researchers to examine inclusion, participation, power and positionality at each stage of the data process. This lens bridges computational and interpretive approaches and informs the standards proposed in this paper.

2.3 EMPIRICAL REVIEW

2.3.1 Satellite imagery, night-time lights and poverty mapping

The largest body of evidence concerns satellite-based estimation of welfare. CNNs trained on medium-resolution imagery outperformed human experts in ranking Tanzanian survey clusters (Sarmadi et al., 2024). Models combining freely available spatial data estimated wealth levels across 59 countries with reasonable accuracy, performing best in lower-income countries, but estimated changes in wealth poorly (Marty & Duhaut, 2024). A continental settlement map validated against survey labels reached about 65% overall accuracy (Kakooei et al., 2026). In East Africa, ML predictions for unsurveyed areas overestimate welfare in poor, rural and single-sector economies and underestimate it in wealthier, urbanised and diversified ones, and spatial models offer only marginal gains where models are weakest (Ru et al., 2026). Night-time lights alone proved a weak proxy for provincial GDP in Egypt until supplemented by population and crop data (Suleiman, 2024), and in Germany a daytime-imagery proxy outperformed night lights, with the advantage growing for smaller units (Lehnert et al., 2023). In Nigeria, night-light and population grids

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have been used to estimate local Gini values that show a north–south gradient (Maduako et al., 2025), and in India comparable methods predict village-level inequality with about 84% accuracy (Pradhan & Agrawal, 2025).

2.3.2 Urban deprivation and the perspective of residents

Studies of urban deprivation show both the reach and the limits of transferability. Models of deprived areas in Accra, Lagos and Nairobi exceeded 80% accuracy within cities, but transfer from Nairobi to Lagos was the exception to otherwise successful cross-city transfer, and a pooled model performed worst for Lagos (Owusu et al., 2023). In Nairobi's informal settlements, an approach that trained models on residents' own pairwise judgements of where it is best to live showed that satellite-based AI can predict locally defined deprivation perceptions (Abascal et al., 2024), an important demonstration that the construct itself can be defined by those measured.

2.3.3 Phone surveys, platform recruitment and digital traces

Remote data collection by phone and platform has expanded rapidly. A scoping review of computer-assisted mobile-phone interviewing in low- and middle-income countries found samples skewed towards more educated, wealthier, urban and male respondents, with coverage problems that weighting cannot fully correct (Greenleaf et al., 2026). Facebook-advertisement recruitment in Kenya, Mexico and Indonesia produced fast, cheap samples that were more educated than national populations (Rosenzweig et al., 2025). Digital traces also depend on platform and state decisions: during Nigeria's 2021 Twitter suspension, 83% of surveyed students reported using VPNs to keep access (Mohammed & Adelakun, 2023), a reminder that the population visible in platform data can change abruptly.

2.3.4 Social-media text and conflict event data

Computational analysis of African social-media text is growing. Over one million Nigerian tweets were collected to study hate speech, with a coded sample showing hateful content rising during electioneering (Ridwanullah et al., 2025). An analysis of more than one million tweets on Ethiopia's #NoMore movement found that Amharic tweets centred on domestic concerns with greater emotional intensity, while English tweets and United States-based users had greater measured influence (Zeleke et al., 2026). In Mali, a mixed-methods study combining network analysis of about 10.7 million tweets with digital ethnography and participatory workshops showed a network dominated by state-affiliated accounts (de Bruijn et al., 2025). Conflict event data, widely used to measure African violence, depend on scope conditions, sources and coding choices that change answers to basic questions about where violence is rising (Raleigh et al., 2023). Öberg and Yilmaz (2025) attribute most differences between leading datasets to auxiliary coding rules and source evaluation, while Broache et al. (2025) show that conservative coding undercounts government killings of civilians, including in Ethiopia. Using such data, Dorward (2024) finds that the "urbanisation of conflict" in sub-Saharan Africa is not borne out.

2.3.5 Algorithmic targeting, digital identity and data governance

ML is increasingly used to decide who receives assistance. In Malawi and Tanzania, label bias from recall-based consumption measures and unstable proxy-means weights led to substantial underestimation of welfare losses from targeting errors, with smaller households most disadvantaged (Dietrich et al., 2024). In Malawi, a simple heuristic based on past survey results predicted food insufficiency about as well as ML models, because insufficiency persists in the same places (Tomes et al., 2025). A study of Pakistan's flood cash programme, whose review also covers African cases such as Togo and Nigeria, found that algorithmic enrolment filters excluded eligible people (Kemal, 2026). Digital identity systems, on which such targeting increasingly relies, carry structural risks of exclusion and surveillance (Wodajo, 2024), and weak legal drafting undermined public trust in Kenya's system (Kabata, 2024). Cross-border research data flows are governed by heterogeneous national laws in Africa (Staunton et al., 2025), and African health researchers face capacity, legal and funding barriers to data sharing (Obiora et al., 2024).

2.3.6 Large language models as measurement instruments

LLMs are now proposed as substitutes for survey respondents. Synthetic responses reproduce average opinions but with far less variance than humans and with unstable estimates across prompts and time

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(Bisbee et al., 2024); generative models display a consistent but unpredictable "machine bias" (Boelaert et al., 2025); and correspondence with human responses is weaker for non-Western samples (Shrestha et al., 2024). Africa is barely represented in this testing literature, which is itself a coverage problem.

2.4 GAP IN THE LITERATURE

Three gaps emerge. First, evaluations of computational measures focus overwhelmingly on predictive accuracy, while coverage, construct validity and reflexivity are discussed separately, if at all. Second, little work traces the policy consequences of computational measurement in Africa: who is excluded, misallocated or made invisible when such measures drive decisions. Third, the relationship between computational and interpretive African social science is rarely theorised; computational studies seldom draw on the ethnographic and historical knowledge that could validate or challenge their proxies. This paper addresses these gaps.

3. MATERIALS AND METHODS

3.1 RESEARCH DESIGN

The study is a methodological and theoretical critique built on an integrative review of peer-reviewed literature. It does not collect primary data. An integrative design was used because relevant evidence is distributed across remote sensing, development economics, political methodology, survey methodology, critical data studies, law and African studies, and must be synthesised conceptually rather than pooled statistically. The analytical approach is abductive: recurrent problems reported across studies were compared, organised into a framework, and formalised as propositions.

3.2 POPULATION AND SAMPLE

The population comprised peer-reviewed journal articles published between 2023 and 2026 on the computational measurement of social phenomena (poverty, inequality, population, settlement, conflict, opinion and eligibility for assistance), on remote and digital data collection, and on the governance of data and algorithms, with priority to studies of Africa and Nigeria. Studies from other regions were admitted where they offered methodological leverage, for example on proxy validity or LLM-based measurement. Sampling was purposive and guided by the three problems of the framework. The final sample comprised 41 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 online, between 2023 and 2026; (c) addressed computational measurement, digital data collection or data governance; and (d) could be verified against the publisher's own record, with an accessible abstract sufficient to report findings accurately. Studies were excluded if they were conference proceedings (including proceedings papers published in journals), editorials or commentaries, dissertations, preprints, working papers or reports; if they were published before 2023; or if their bibliographic details or findings could not be confirmed from the publisher record.

3.4 DATA COLLECTION

Searches were conducted in October 2026 through scholarly web search and the platforms of academic publishers (including Sage, Oxford University Press, Cambridge University Press, Springer Nature, MDPI and the National Academy of Sciences). Search strings combined method terms (*satellite imagery*, *night-time lights*, *mobile phone data*, *call detail records*, *social media*, *Twitter*, *machine learning*, *large language models*, *proxy means test*, *gridded population*, *conflict event data*) with context terms (*Africa*, *sub-Saharan*, *Nigeria*, *Kenya*, *Ethiopia*, *Malawi*, *Global South*) and problem terms (*bias*, *validity*, *representativeness*, *targeting*, *data governance*, *data sovereignty*).

3.5 VERIFICATION AND BASES OF JUDGEMENT

Each candidate article was checked against its publisher page for title, authors, year, journal, volume, issue, pagination or article number, and DOI, and inspected for retractions, corrections or expressions of concern. One included article carries a published correction to its competing-interests statement (Raleigh et al., 2023), which does not affect its findings; no other notices were found. Of 73 candidate records that reached full-record verification, 41 were included and 32 were excluded (Table 1). Publisher pages for 13 candidates, mainly

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on two large publishing platforms, could not be accessed during the verification window, so those articles were excluded rather than cited unverified; this is acknowledged as a limitation. Pre-screening exclusions were not counted systematically. Relevance was judged by whether a study reported evidence on coverage, construct validity, reflexivity or the policy and governance consequences of computational measurement.

Table. 1. Summary of source screening and verification

Stage / outcome	Records (n)
Candidate records reaching full-record verification	73
Excluded: publisher record not accessible for confirmation	13
Excluded: abstract/findings or full author list not accessible	6
Excluded: published before 2023	5
Excluded: conference proceedings paper (incl. in journals)	4
Excluded: editorial or commentary	2
Excluded: dissertation	1
Excluded: outside scope of review	1
Included in final sample	41

Note. All included articles were confirmed against publisher records in October 2026. One carries a published correction to its competing-interests statement (Raleigh et al., 2023); no retractions or expressions of concern were found.

3.6 DATA ANALYSIS

Analysis proceeded in three stages. First, the findings of each article were coded against the three provisional problems and against reported policy uses and governance arrangements. Second, codes were compared across data sources (satellite and night-light data, phone and platform data, social-media text, conflict event data, administrative and targeting data, and LLM outputs) to identify recurring patterns, summarised in an evidence map (Table 3). Third, recurring mechanisms were formalised as propositions and integrated into a framework (Figure 1). Contrary evidence was deliberately sought, for example findings that computational methods outperform human judgement (Sarmadi et al., 2024) or that dataset differences have been overstated (Öberg & Yilmaz, 2025).

3.7 VARIABLE MEASUREMENT

Although the paper is conceptual, its constructs are defined so that they can be assessed in future empirical audits of computational measures. Table 2 presents operational definitions and indicators.

Table. 2. Constructs, operational definitions and audit indicators

Construct	Operational definition	Audit indicators
Coverage	Overlap between those represented in the source data and the target population	Share of target population represented; representation gaps by gender, age, wealth, education and urban–rural status; areas without training labels
Construct validity	Degree to which the proxy captures the concept across places, scales and time	Explicit proxy–concept argument; accuracy on levels vs. changes; out-of-area and out-of-time transfer; agreement with locally defined ground truth
Reflexivity	Extent to which producing or using the measure changes what is measured	Policy uses of the measure; behavioural or institutional responses; changes in data availability or access; trust and grievance indicators
Policy consequence	Distribution of errors when the measure informs decisions	Inclusion and exclusion errors by group; welfare-weighted targeting losses; existence of appeal mechanisms
Measurement authority	Who owns, controls and validates the data and models	Data ownership; national statistical office involvement; legal compliance; African authorship and leadership

3.8 RELIABILITY, VALIDITY AND TRUSTWORTHINESS

Because the study is interpretive, trustworthiness criteria were applied. *Credibility* was supported by verifying every source against its publisher record and reporting only what sources state. *Dependability* was supported by documenting search terms, criteria and screening outcomes. *Confirmability* was supported by seeking evidence that contradicts the critique. *Transferability* is bounded: the framework is grounded in African evidence and comparative methodological studies 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. The author(s) reviewed, revised and take full

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responsibility for the content and interpretations. No AI tool is listed as an author. The study analysed published literature only; no human participants were involved and ethical approval was not required. All sources are listed in the references; no new datasets or code were generated.

4. RESULTS AND DISCUSSION

4.1 RESULTS

4.1.1 Evidence map across data sources

Table 3 summarises how each family of computational data performs on the three problems, as reported in the sampled studies. The assessments are qualitative syntheses, not scores.

Table. 3. Evidence map: data sources on the three problems

Data source	Coverage	Construct validity	Reflexivity / policy
Satellite imagery and night lights	Training labels from surveys; weakest in poor, rural areas (Ru et al., 2026)	Good for levels, poor for change (Marty & Duhaut, 2024); NTL weak alone (Suleiman, 2024)	Population counts shift to private providers (Darin, 2025)
Phone and platform samples	Skew educated, urban, male (Greenleaf et al., 2026; Rosenzweig et al., 2025)	Weaker for complex or numeric items (Greenleaf et al., 2026)	Platform bans alter who is visible (Mohammed & Adelakun, 2023)
Social-media text	Language and location divides (Zeleke et al., 2026)	Needs human coding and context (Ridwanullah et al., 2025; de Bruijn et al., 2025)	Networks reproduce state-centred hierarchies (de Bruijn et al., 2025)
Conflict event data	Source- and scope-dependent (Raleigh et al., 2023)	Coding rules drive differences (Öberg & Yilmaz, 2025)	Statist bias undercounts state violence (Broache et al., 2025)
Targeting and identity data	Label and recall bias (Dietrich et al., 2024)	Simple survey heuristics match ML (Tomes et al., 2025)	Algorithmic exclusion; trust deficits (Kemal, 2026; Kabata, 2024)
LLM outputs	Weaker fit for non-Western samples (Shrestha et al., 2024)	Low variance, unstable bias (Bisbee et al., 2024; Boelaert et al., 2025)	Risk of replacing African voices

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

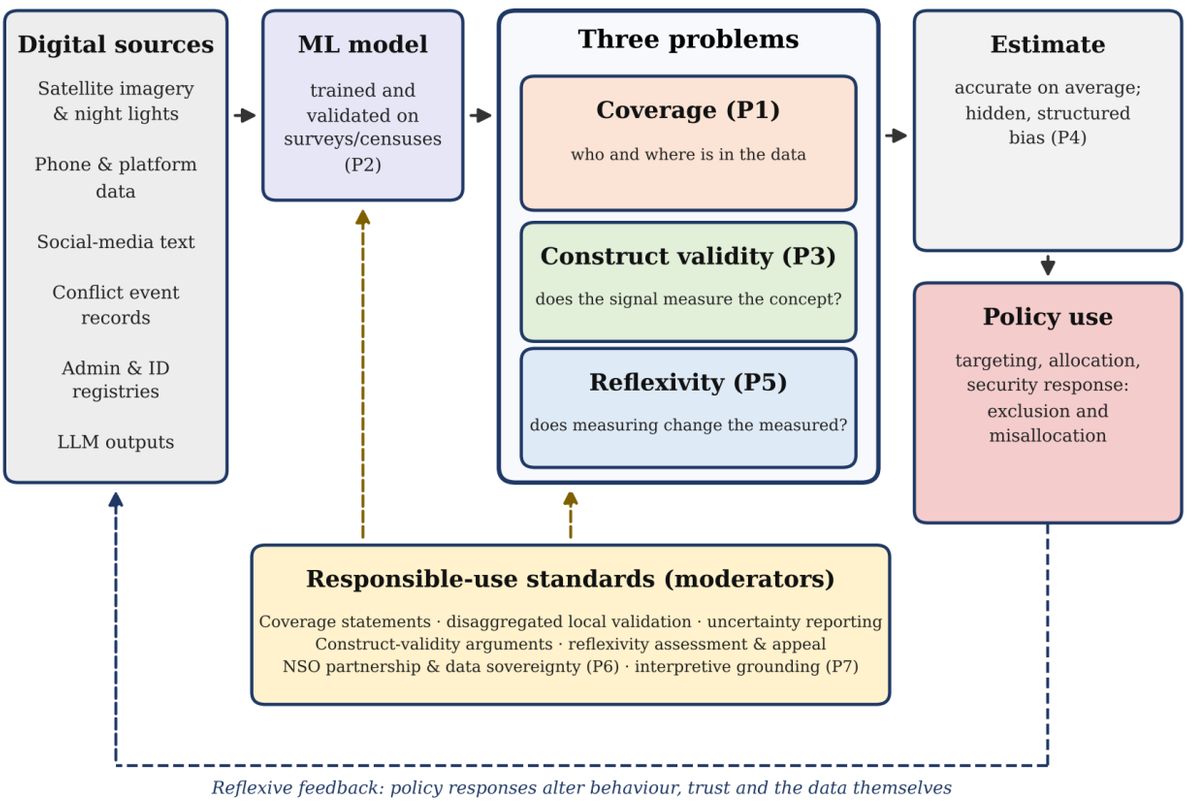
Three patterns emerge. First, coverage gaps are not random: across phone surveys, platform samples and satellite models, the people and places least represented are poorer, more rural, less educated or female, which is to say the populations that social policy most needs to see. Second, construct validity is strongest when the proxy is physically close to the concept (settlement and building patterns for settlement type) and weakest when the distance is large (night lights for inequality, tweets for opinion, recorded events for violence). Third, reflexivity is least studied but most consequential: wherever computational measures enter policy, as in targeting, digital identity or platform regulation, they alter incentives, trust and the data themselves.

4.1.2 The coverage–validity–reflexivity framework

Figure 1 presents the framework. Digital sources (satellite and night-light imagery, phone and platform data, social-media text, conflict event records, administrative and identity registries, and LLM outputs) are processed by ML models that are typically trained and validated on household surveys or censuses. Three problems intervene between the data and the resulting measure. *Coverage* determines who and where is represented. *Construct validity* determines whether the signal measures the concept of interest across places and times. *Reflexivity* determines whether producing and using the measure changes what it measures. The resulting estimates can be accurate on average while carrying hidden, structured bias. When those estimates drive policy (targeting, allocation, security responses), errors become exclusions and misallocations, and the policy response itself feeds back into the data. Responsible-use standards, discussed below, moderate each link.

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Figure. 1. The coverage–validity–reflexivity framework for computational measurement of African societies



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.

Proposition 1 (structured coverage). Computational measures are valid for African populations only to the extent that the coverage of their source data overlaps the population of interest; because coverage gaps correlate with poverty, rurality, gender and education, unadjusted computational estimates systematically misrepresent the most deprived. Evidence from phone surveys (Greenleaf et al., 2026), platform recruitment (Rosenzweig et al., 2025) and satellite welfare models (Ru et al., 2026) supports this proposition.

Proposition 2 (inherited labels). Because ML proxies are trained on surveys and censuses, they inherit the coverage, timeliness and label errors of those sources; computational methods therefore extend rather than replace conventional data, and their quality cannot exceed that of their training labels. Label bias in consumption data (Dietrich et al., 2024), dependence on survey clusters (Sarmadi et al., 2024) and the persistence-driven success of simple survey-based heuristics (Tomes et al., 2025) illustrate the point.

Proposition 3 (proxy distance). The greater the conceptual distance between an observable signal and the concept it represents, the less a computational measure will transfer across places, scales and time. Night lights are weak alone for regional output (Suleiman, 2024) and weaker for small units (Lehnert et al., 2023); models of urban deprivation transfer least well to Lagos (Owusu et al., 2023); conflict-risk models degrade when conflict geography shifts (Goodman et al., 2024); and wealth changes are predicted far less well than wealth levels (Marty & Duhaut, 2024).

Proposition 4 (invisible bias). The errors of computational measures are harder to detect than those of surveys, because they are spatially structured, rarely reported with uncertainty and embedded in pipelines that users do not inspect; validity therefore requires local, disaggregated validation rather than aggregate accuracy. Spatially patterned errors (Ru et al., 2026), dataset-dependent

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conclusions about violence (Raleigh et al., 2023; Broache et al., 2025), thin validation practices (Park & Montgomery, 2026) and the low variance and unstable bias of LLM "respondents" (Bisbee et al., 2024; Boelaert et al., 2025) support this proposition.

Proposition 5 (reflexivity and policy consequence). When computational measures are used to allocate resources, rights or attention, exclusion errors fall disproportionately on the least visible, and the measures alter the behaviour, trust and data on which they depend. Algorithmic enrolment filters exclude eligible households (Kemal, 2026; Dietrich et al., 2024); prediction steers present decisions (Lazaro & Rizzi, 2023); weak legal frameworks erode trust in identity systems (Kabata, 2024; Wodajo, 2024); and state action can reshape the population visible on platforms (Mohammed & Adelakun, 2023).

Proposition 6 (measurement authority). Where source data and models are privately owned or externally produced, authority over the measurement of African societies shifts from national statistical systems and African publics to external actors, with consequences for accountability and for the questions that are asked. Commodified demographic figures (Darin, 2025), uneven datafication (Akbari, 2026), dependence in AI governance (Okocha & Zoho, 2026), fragmented data-sharing law (Staunton et al., 2025), barriers facing African researchers (Obiora et al., 2024) and persistent North–South inequities in authorship (Ofori et al., 2026) support this proposition.

Proposition 7 (complementarity). Computational measures are most valid when their constructs, labels and interpretations are grounded in interpretive and local knowledge. Defining deprivation through residents' own judgements (Abascal et al., 2024), combining network analysis with ethnography and participatory workshops (de Bruijn et al., 2025), pairing algorithmic and human coding (Ridwanullah et al., 2025) and distinguishing local-language from English discourse (Zeleke et al., 2026) show how interpretive work changes what computational measures capture.

4.1.4 The Nigerian illustration

Nigeria illustrates each problem. It is a frequent site of computational measurement: night-light inequality maps for every local government area (Maduako et al., 2025), deprivation mapping in Lagos (Owusu et al., 2023), satellite-based conflict-risk prediction (Goodman et al., 2024) and large-scale analysis of political hate on Twitter/X (Ridwanullah et al., 2025). Coverage is uneven, as phone- and platform-based samples skew towards the educated and urban (Greenleaf et al., 2026). Construct validity is fragile, as models that work elsewhere transfer poorly to Lagos and conflict models degrade when violence moves. Reflexivity is visible: the 2021 suspension of Twitter altered how and whether Nigerians appeared in platform data (Mohammed & Adelakun, 2023). Under these conditions, computational estimates are valuable for exploration but should be treated with caution as a basis for allocation.

4.2 DISCUSSION

The framework reframes the debate between enthusiasts and critics of computational social science in Africa. Enthusiasts are right that new methods can see what surveys cannot and, on some tasks, outperform expert judgement (Sarmadi et al., 2024). Critics are right that data-driven systems can reproduce inequality (Akbari, 2026; Darin, 2025). The coverage–validity–reflexivity framework suggests that both positions are partial: the validity of a computational measure is not a property of the method but of the match between data, construct and context, and of what is done with the result.

The findings qualify the common claim that computational methods "fill data gaps." They fill gaps in *time and space* but not in *information*: because models are trained on surveys, they redistribute existing information rather than create new ground truth (Proposition 2). This explains why predictions of change are weaker than predictions of levels (Marty & Duhaut, 2024) and why simple heuristics based on past surveys can match ML (Tomes et al., 2025). It also implies that investment in computational methods cannot substitute for investment in surveys, censuses and national statistical capacity (Dang et al., 2024; Dindi & Stiegler, 2025).

The debate over conflict data offers a useful lesson. Raleigh et al. (2023) argue that dataset scope, sources and coding choices change substantive conclusions, while Öberg and Yilmaz (2025) attribute differences mainly to coding rules and dispute the critique's

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emphasis on sourcing. Both positions agree that *design choices are consequential and must be made visible*, which is the core of Proposition 4. The finding that conservative coding undercounts state violence (Broache et al., 2025) shows how such choices can align measurement with the perspective of the powerful.

On reflexivity, the evidence suggests that the most serious risks arise not in research but in policy use. When targeting relies on biased labels, welfare losses are underestimated and particular household types are excluded (Dietrich et al., 2024); when enrolment depends on algorithmic filters, eligible people fall through (Kemal, 2026). Prediction does not simply inform such decisions but reorganises how the future is governed (Lazaro & Rizzi, 2023). African data protection and identity law is developing (Kabata, 2024; Staunton et al., 2025), but individual privacy rights may not match the structural character of these risks (Wodajo, 2024).

On the relationship between computational and interpretive African social science, the evidence supports complementarity rather than replacement. The most convincing studies in the sample are those that let local knowledge define constructs or interpret patterns (Abascal et al., 2024; de Bruijn et al., 2025). This accords with calls for a critical data science that builds reflexivity and participation into every stage (van Geene et al., 2026). Interpretive scholars are not merely users of computational outputs; they are needed to specify what is measured and to judge whether measures make sense.

The paper has limitations. It is a conceptual synthesis, and its propositions require testing. The evidence base was restricted to verified 2023–2026 journal articles, which excludes foundational work and much influential grey literature, including several well-known evaluations of phone-data targeting that appear in working papers or could not be verified. Access constraints prevented verification of some relevant journal articles, which were excluded. Mobile-phone call-detail-record research on Africa is under-represented in the verified sample. Future research should audit specific computational measures against the indicators in Table 2, compare model errors across disaggregated groups and places, and study the downstream effects of computational targeting on excluded households.

5. CONCLUSION AND RECOMMENDATION

Computational social science offers African research and policy genuine advances in timeliness and spatial detail. But its measures are only as good as their coverage, their construct validity and their handling of reflexivity, and their errors are harder to see than those of the surveys they supplement. The structured nature of these errors means that the most deprived are the most likely to be misrepresented, and the use of such measures in policy turns error into exclusion. The relationship between computational and interpretive African social science should therefore be one of mutual dependence.

The paper proposes seven standards for responsible use. **First**, every computational study of an African population should include a *coverage statement* that identifies who is under-represented in the source data and how that affects inference. **Second**, models should be *validated locally and disaggregated* by place, gender, urban–rural status and wealth, with uncertainty reported for every estimate used in decisions. **Third**, authors should provide an explicit *construct-validity argument* linking proxy to concept, supported where possible by ground truth collected for the purpose. **Fourth**, any use of computational measures for allocation should be preceded by an *impact and reflexivity assessment* and accompanied by grievance and appeal mechanisms for those excluded. **Fifth**, research should be conducted in partnership with *national statistical offices* and comply with national data protection law, with data and models retained or shared on terms that preserve public authority over population figures. **Sixth**, research teams should include *African researchers in leading roles* and combine computational analysis with interpretive and participatory methods. **Seventh**, *LLM-generated responses* should not be used as substitutes for African survey respondents until their validity for African populations has been demonstrated.

6. CONTRIBUTION TO EXISTING KNOWLEDGE

The paper makes four contributions. **Conceptually**, it integrates scattered critiques into a single coverage–validity–reflexivity framework applicable across satellite, phone, platform, text, event, administrative and LLM data. **Theoretically**, it links measurement theory, critical data studies and science

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and technology studies to explain why computational errors are structured and hard to see, and it specifies the complementary relationship between computational and interpretive African social science. **Empirically**, it consolidates recent verified evidence from Africa, including Nigeria, into an evidence map and a set of indicators for auditing computational measures. **Methodologically and for policy**, it proposes seven standards for the responsible use of big data and ML in research on African societies, including coverage statements, disaggregated validation, reflexivity assessments and partnership with national statistical systems.

7. REFERENCES

Abascal, A., Vanhuysse, S., Grippa, T., Rodriguez-Carreño, I., Georganos, S., Wang, J., Kuffer, M., Martinez-Diez, P., Santamaria-Varas, M., & Wolff, E. (2024). AI perceives like a local: Predicting citizen deprivation perception using satellite imagery. *npj Urban Sustainability, 4*, Article 20. https://doi.org/10.1038/s42949-024-00156-x

Akbari, A. (2026). Uneven datafication. *Dialogues on Digital Society, 2*(2), 158–180. https://doi.org/10.1177/29768640261439961

Bisbee, J., Clinton, J. D., Dorff, C., Kenkel, B., & Larson, J. M. (2024). Synthetic replacements for human survey data? The perils of large language models. *Political Analysis, 32*(4), 401–416. https://doi.org/10.1017/pan.2024.5

Boelaert, J., Coavoux, S., Ollion, É., Petev, I., & Präg, P. (2025). Machine bias. How do generative language models answer opinion polls? *Sociological Methods & Research, 54*(3), 1156–1196. https://doi.org/10.1177/00491241251330582

Broache, M. P., Cronin-Furman, K., Lake, M., & Yu, A. (2025). The uncounted dead: Statist bias and civilian targeting in conflict data. *Journal of Global Security Studies, 10*(3), Article ogaf013. https://doi.org/10.1093/jogss/ogaf013

Dang, H.-A. H., Jolliffe, D., Serajuddin, U., & Stacy, B. (2024). Country statistical capacity: A recent assessment tool and further reflections on the way forward. *Statistical Journal of the IAOS, 40*(2), 211–225. https://doi.org/10.3233/SJI-230093

Darin, E. (2025). Demographic figures at risk in the digital era: Resisting commodification, reclaiming the common good. *Big Data & Society, 12*(4). https://doi.org/10.1177/20539517251403948

de Bruijn, M., Mutsvairo, B., Bruls, L., Cissé, M. G., Langguth, J., Orgeret, K. S., Badji, S. D., Moges, M. A., & Schroeder, D. T. (2025). "Aren't we all journalists?" Citizen journalism, disinformation and the weaponization of social media in conflict torn Mali. *Journalism, 26*(5), 1027–1046. https://doi.org/10.1177/14648849241312743

Dietrich, S., Malerba, D., & Gassmann, F. (2024). Predicting social assistance beneficiaries: On the social welfare damage of data biases. *Data & Policy, 6*, Article e3. https://doi.org/10.1017/dap.2023.38

Dindi, P. D., & Stiegler, N. (2025). Charting the future of censuses: Insights, lessons and recommendations for the 2030 round. *Statistical Journal of the IAOS, 41*(2), 402–420. https://doi.org/10.1177/18747655251335763

Dorward, N. (2024). The urbanization of conflict? Patterns of armed conflict and protest in Africa. *African Affairs, 123*(493), 468–501. https://doi.org/10.1093/afraf/adae025

Goodman, S., BenYishay, A., & Runfola, D. (2024). Spatiotemporal prediction of conflict fatality risk using convolutional neural networks and satellite imagery. *Remote Sensing, 16*(18), Article 3411. https://doi.org/10.3390/rs16183411

Greenleaf, A. R., Diakabana, H., & Lau, C. (2026). Computer-assisted mobile phone interviews in low- and middle-income countries through a total survey error framework. *Public Opinion Quarterly, 90*(3), 878–910. https://doi.org/10.1093/poq/nfag023

Kabata, V. (2024). An assessment of the legal and regulatory framework supporting the implementation of the National Integrated Identity Management System (NIIMS) in

© IIARJournal. All rights reserved.

Kenya. *Data & Policy, 6*, Article e7. https://doi.org/10.1017/dap.2023.36

Kakooei, M., Bailie, J., Pettersson, M. B., Söderberg, A., Becevic, A., & Daoud, A. (2026). A high resolution urban and rural settlement map of Africa using deep learning and satellite imagery. *Scientific Reports, 16*, Article 637. https://doi.org/10.1038/s41598-025-34295-7

Kemal, A. A. (2026). Data, algorithmic targeting, and artificial intelligence (AI) technologies in adaptive social cash systems: Towards an AI governance framework. *Data & Policy, 8*, Article e12. https://doi.org/10.1017/dap.2026.10057

Knorr, C., & Pentzold, C. (2025). Making sense of "big data": Ten years of discourse around datafication. *Big Data & Society, 12*(2). https://doi.org/10.1177/20539517251330181

Lazaro, C., & Rizzi, M. (2023). Predictive analytics and governance: A new sociotechnical imaginary for uncertain futures. *International Journal of Law in Context, 19*(1), 70–90. https://doi.org/10.1017/S1744552322000477

Lehnert, P., Niederberger, M., Backes-Gellner, U., & Bettinger, E. (2023). Proxying economic activity with daytime satellite imagery: Filling data gaps across time and space. *PNAS Nexus, 2*(4), Article pgad099. https://doi.org/10.1093/pnasnexus/pgad099

Maduako, I. N., Nkwunonwo, U. C., Oluoma, C. C., Moka, E. C., Nwachukwu, W. C., Oha, V. O., & Stephen, O. O. (2025). Geospatial mapping of economic inequality distribution in Nigeria at the lowest administrative unit level based on night light data. *Transactions in Earth, Environment, and Sustainability, 3*(2), 93–105. https://doi.org/10.1177/2754124X251387532

Marty, R., & Duhaut, A. (2024). Global poverty estimation using private and public sector big data sources. *Scientific Reports, 14*, Article 3160. https://doi.org/10.1038/s41598-023-49564-6

Mohammed, A., & Adelakun, L. A. (2023). The 2021 Nigerian Twitter ban: A text-analytics and survey insight into public reactions and outcomes in the early weeks of the ban. *Communication and the Public, 8*(4), 390–401. https://doi.org/10.1177/20570473231209077

Öberg, M., & Yilmaz, M. C. (2025). Measurement issues in conflict event data: Addressing some misconceptions about what drives differences between human-coded event datasets. *Research & Politics, 12*(3). https://doi.org/10.1177/20531680251362440

Obiora, O. L., Shead, D. A., & Olivier, B. (2024). Data sharing considerations and practice among health researchers in Africa: A scoping review. *Digital Health, 10*. https://doi.org/10.1177/20552076241290955

Ofori, F., Matos, S., & Tavalaei, M. (2026). Digital poverty in the Global South. *Management and Organization Review, 22*(4), 718–742. https://doi.org/10.1017/mor.2025.10117

Okocha, D. O., & Zoho, J. T. (2026). Is Africa being recolonized in the era of technological advancements? Critiquing Africa's sovereignty in the era of artificial intelligence. *Journal of World Affairs, 2*(2), 181–201. https://doi.org/10.1177/29769442261448656

Owusu, M., Engstrom, R., Thomson, D., Kuffer, M., & Mann, M. L. (2023). Mapping deprived urban areas using open geospatial data and machine learning in Africa. *Urban Science, 7*(4), Article 116. https://doi.org/10.3390/urbansci7040116

Park, J. Y., & Montgomery, J. M. (2026). Toward a framework for creating trustworthy measures with supervised machine learning for text. *Political Science Research and Methods, 14*(4), 1252–1268. https://doi.org/10.1017/psrm.2025.10042

Pradhan, N., & Agrawal, A. (2025). Mapping fine-scale socioeconomic inequality using machine learning and remotely sensed data. *PNAS Nexus, 4*(2), Article pgaf040. https://doi.org/10.1093/pnasnexus/pgaf040

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Raleigh, C., Kishi, R., & Linke, A. (2023). Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices. *Humanities and Social Sciences Communications, 10*, Article 74. https://doi.org/10.1057/s41599-023-01559-4 (Correction published 2023, *10*, Article 123, https://doi.org/10.1057/s41599-023-01626-w)

Ridwanullah, A. O., Sule, S. Y., Usman, B., & Abdulsalam, L. U. (2025). Politicization of hate and weaponization of Twitter/X in a polarized digital space in Nigeria. *Journal of Asian and African Studies, 60*(5), 3350–3370. https://doi.org/10.1177/00219096241230500

Rosenzweig, L. R., Bergquist, P., Hoffmann Pham, K., Rampazzo, F., & Mildenberger, M. (2025). Survey sampling in the Global South using Facebook advertisements. *Political Science Research and Methods*, *13*, 781–797. https://doi.org/10.1017/psrm.2025.18

Ru, Y., Tennant, E., Matteson, D. S., & Barrett, C. B. (2026). Spatial heterogeneity in machine learning-based poverty mapping: Where do models underperform? *Geography and Sustainability, 7*(2), Article 100413. https://doi.org/10.1016/j.geosus.2026.100413

Sarmadi, H., Wahab, I., Hall, O., Rögnvaldsson, T., & Ohlsson, M. (2024). Human bias and CNNs' superior insights in satellite based poverty mapping. *Scientific Reports*, *14*, Article 22878. https://doi.org/10.1038/s41598-024-74150-9

Shrestha, P., Krpan, D., Koaik, F., Schnider, R., Sayess, D., & Binbaz, M. S. (2024). Beyond WEIRD: Can synthetic survey participants substitute for humans in global policy research? *Behavioral Science & Policy, 10*(2), 26–45. https://doi.org/10.1177/23794607241311793

Staunton, C., Edgcumbe, A., Abdulrauf, L., Gooden, A., Ogendi, P., & Thaldar, D. (2025). Cross-border data sharing for research in Africa: An analysis of the data protection and research ethics requirements in 12 jurisdictions. *Journal of Law and the Biosciences, 12*(1), Article lsaf002. https://doi.org/10.1093/jlb/lsaf002

Suleiman, H. (2024). Illuminating the Nile: Estimating subnational GDP in Egypt using nighttime lights and machine learning. *GeoJournal, 89*, Article 117. https://doi.org/10.1007/s10708-024-11106-6

Tomes, A., Gholami, S., Alia, D., Hennessy, C., Xu, D., Bitz, C., Dodhia, R., Lavista Ferres, J., & Anderson, C. L. (2025). Assessing the utility of machine learning for predicting food sufficiency: A case study in Malawi. *Data & Policy, 7*, Article e52. https://doi.org/10.1017/dap.2025.10013

van Geene, L., Goncalves, J., Robinson, C., & Verma, T. (2026). Reclaiming data science for just geographies: A critical approach. *Big Data & Society, 13*(2). https://doi.org/10.1177/20539517261426463

Wodajo, K. (2024). Societal and structural risks of biometric ID: Towards people's right to privacy. *Science, Technology and Society, 29*(4), 614–631. https://doi.org/10.1177/09717218241281941

Zeleke, M., Hong, L., & Smith, D. (2026). Global and local voices: Analyzing the dichotomy of social media discourse in Ethiopian social movement #NoMore. *Data & Policy*, *8*, Article e6. https://doi.org/10.1017/dap.2026.10054

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