Improving Economics and Finance in Sub-Saharan Africa using Deep Learning and Machine Learning Models: A Systematic Review

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Abstract

Purpose of review: This systematic review aims to map the current landscape of Artificial Intelligence (AI) and Machine Learning (ML) applications within economics and finance in sub-Saharan Africa. It seeks to identify dominant research trends, key application domains, model performance, emerging opportunities, and the significant socio-economic implications of these technologies for the region.

Recent findings: Current research demonstrates a significant surge in AI and ML adoption in African economics and finance, particularly since 2017. Key applications include: (1) poverty and economic well-being prediction using satellite imagery and alternative data sources, with models explaining over 70% of the variation in village-level wealth; (2) real-time economic nowcasting to track the impacts of major events like the COVID-19 pandemic; and (3) enhancing financial inclusion and risk management through AI-driven credit scoring and fraud detection, where models achieve F1-scores exceeding 0.80. Deep learning (DL) models, especially Convolutional Neural Networks (CNNs) for geospatial data and Recurrent Neural Networks (RNNs) for time-series forecasting, are pivotal.

Summary: AI and ML are transforming economics and finance in sub-Saharan Africa by providing scalable, high-frequency, and granular data that bypasses traditional data gaps. These technologies offer transformative potential for evidence-based policymaking, financial stability, and inclusive growth. However, significant challenges persist, including data sparsity, infrastructural limitations, and the risk of algorithmic bias. Future advancements depend on developing localized, context-aware models, investing in data infrastructure, and establishing robust ethical governance frameworks to ensure equitable outcomes.

Keywords: artificial intelligence; economic forecasting; financial inclusion; governance; nowcasting; poverty mapping; satellite imagery

1. Introduction

Sub-Saharan Africa represents one of the world's most dynamic yet challenging economic regions, characterized by rapid demographic transitions, technological leapfrogging, and persistent developmental bottlenecks (Jayne et al., 2018). The region's economic landscape encompasses a complex tapestry of rapid urbanization, emerging digital economies, and structural vulnerabilities including widespread poverty, deepening inequality, and extensive financial exclusion (Bhorat et al., 2016; European Investment Bank, 2024; Azzarri and Signorelli, 2020). These multifaceted challenges are compounded by what economists term "data poverty" – the chronic scarcity of timely, reliable, and granular economic information necessary for evidence-based policymaking and effective resource allocation (Bigman and Fofack, 2000).

Traditional economic data collection mechanisms in Sub-Saharan Africa face numerous constraints. National statistical systems often operate with limited resources, conducting household surveys and censuses infrequently – sometimes with gaps of five to ten years between major data collection exercises (Batana, 2013; Berenger, 2019). This temporal sparsity is further complicated by spatial limitations, as rural and remote areas frequently remain underrepresented in official statistics (Abeje et al., 2020). The resulting information gaps create significant obstacles for governments, central banks, multilateral institutions, and private sector actors seeking to design targeted interventions, assess policy impacts, or make informed investment decisions (International Monetary Fund, 2020a; International Monetary Fund, 2021).

The emergence of the Fourth Industrial Revolution, as conceptualized by Schwab (2016), has catalyzed a paradigmatic shift in how economic data can be generated, processed, and analyzed. Artificial Intelligence (AI) and Machine Learning (ML) technologies now offer unprecedented capabilities to extract economic insights from diverse, non-traditional data sources (Makridakis, 2017; Vassakis et al., 2017). These range from high-resolution satellite imagery and mobile phone metadata to financial transaction records, social media sentiment, and web search patterns (Narita and Yin, 2018). For Sub-Saharan Africa, this technological revolution presents unique opportunities to leapfrog traditional data infrastructure limitations and generate real-time economic intelligence at scales previously unimaginable (Arakpogun et al., 2021; Mienye et al., 2024).

The foundational work establishing AI's potential for economic analysis in African contexts can be traced to several seminal studies. Jean et al. (2016) demonstrated that convolutional neural networks could predict village-level wealth with remarkable accuracy by analyzing publicly available satellite imagery, explaining over 70% of the variation in consumption expenditure across multiple African countries. This groundbreaking research was subsequently extended by Yeh et al. (2020), who developed more sophisticated DL architectures capable of generating continental-scale economic well-being maps using only daytime satellite imagery. These studies established the viability of "poverty from space" approaches that have since become a cornerstone of AI-driven development economics (Ayush et al., 2020, 2021).

Parallel developments in alternative data utilization have further expanded the AI toolkit for African economic analysis. Blumenstock et al. (2015) pioneered the use of mobile phone metadata to predict individual and regional wealth levels in Rwanda, demonstrating that call detail records could serve as proxies for economic activity with accuracy comparable to traditional household surveys. This mobile-data approach has been refined and extended across multiple African contexts (Steele et al., 2017), revealing consistent patterns linking digital behavior to economic outcomes.

The integration of multiple data sources has emerged as a particularly promising frontier. Pokhriyal and Jacques (2017) demonstrated that combining satellite imagery with survey data and mobile phone records could significantly improve poverty prediction accuracy compared to any single data source. Steele et al. (2017) further advanced multi-modal approaches by integrating satellite data with mobile phone records to create high-resolution poverty maps across Bangladesh, with methodologies directly applicable to African contexts.

Beyond poverty measurement, AI applications have expanded into macroeconomic monitoring and financial services. The International Monetary Fund has been at the forefront of applying ML to real-time economic tracking in Sub-Saharan Africa (International Monetary Fund, 2022; Barhoumi et al., 2022). During the COVID-19 pandemic, these approaches proved particularly valuable, with Buell et al. (2021) and Barhoumi et al. (2022) developing novel methodologies to track economic impacts using big data sources when traditional indicators became unreliable or delayed.

In the financial sector, AI applications have focused primarily on expanding access through improved credit scoring and fraud detection. Traditional credit assessment methods often exclude the majority of Sub-Saharan African populations due to limited formal financial histories (Mhlanga and Dzingirai, 2025). However, AI-driven approaches utilizing alternative data sources – including mobile money transactions, utility payments, and social network information – have shown promising results in assessing creditworthiness for previously "unscoreable" populations (Kruppa et al., 2013; Adewuyi et al., 2023).

Agricultural applications represent another critical domain, given agriculture's central role in Sub-Saharan African economies. Remote sensing combined with ML has enabled precision agriculture applications, from crop yield prediction to pest and disease detection (Chemura et al., 2015; Amraoui et al., 2022). These technologies offer particular value for smallholder farmers who constitute the majority of the region's agricultural workforce but have historically lacked access to data-driven farming insights (Hinson et al., 2019).

The rapid proliferation of AI applications in African economics and finance has not occurred without challenges and controversies. Concerns about "digital colonialism" have emerged, with critics arguing that AI development remains concentrated in Western institutions and corporations, potentially perpetuating existing power imbalances (Birhane and Guest, 2020; Etori et al., 2024). The risk of algorithmic bias represents another significant challenge, as models trained on data reflecting historical inequalities may perpetuate or amplify existing disparities (Mohamed et al., 2020; Okolo et al., 2023).

Ethical considerations extend beyond bias concerns to encompass broader questions of data sovereignty, privacy protection, and community consent (Abdilla et al., 2020). The collection and analysis of sensitive economic data – whether from satellite imagery, mobile phones, or financial transactions – raises important questions about who controls these data streams and how they are utilized (Bondi et al., 2021). These concerns have sparked growing interest in "decolonial AI" approaches that prioritize African agency, local capacity building, and culturally appropriate technological development (Mhlambi, 2020; Ayana et al., 2024).

Infrastructure limitations represent a persistent practical challenge. While AI technologies offer promise for leapfrogging traditional data collection methods, they often require substantial computational resources, high-speed internet connectivity, and specialized technical expertise – resources that remain limited across much of Sub-Saharan Africa (Robinson, 2018; Ade-Ibijola and Okonkwo, 2023). The "digital divide" thus poses ongoing obstacles to widespread AI adoption, potentially exacerbating rather than alleviating existing inequalities if not carefully managed (Kolade and Owoseni, 2022).

Despite these challenges, the trajectory of AI adoption in Sub-Saharan African economics and finance appears irreversible. Growing investments in digital infrastructure, expanding educational programs in data science and AI, and increasing policy attention to technology-enabled development suggest that these applications will continue expanding (Ezugwu et al., 2023; Turki et al., 2023). The key question is no longer whether AI will transform economic analysis and financial services in the region, but rather how this transformation can be managed to maximize benefits while minimizing risks and ensuring equitable outcomes (Rashed and Shah, 2021).

2. Materials and Methods

2.1. Literature search strategy

This systematic review was based on the analysis of a dataset comprising 103 scholarly articles related to the application of AI in economics and finance in Sub-Saharan Africa. To ensure a comprehensive and reproducible review, a systematic literature search was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). The literature search aimed to identify peer-reviewed articles, working papers, and institutional reports detailing the application of AI and ML techniques. A systematic search was performed across several major electronic scientific databases, including Scopus, Web of Science, and Google Scholar (**Figure 1**). The search was conducted for publications between 2000 and 2025.

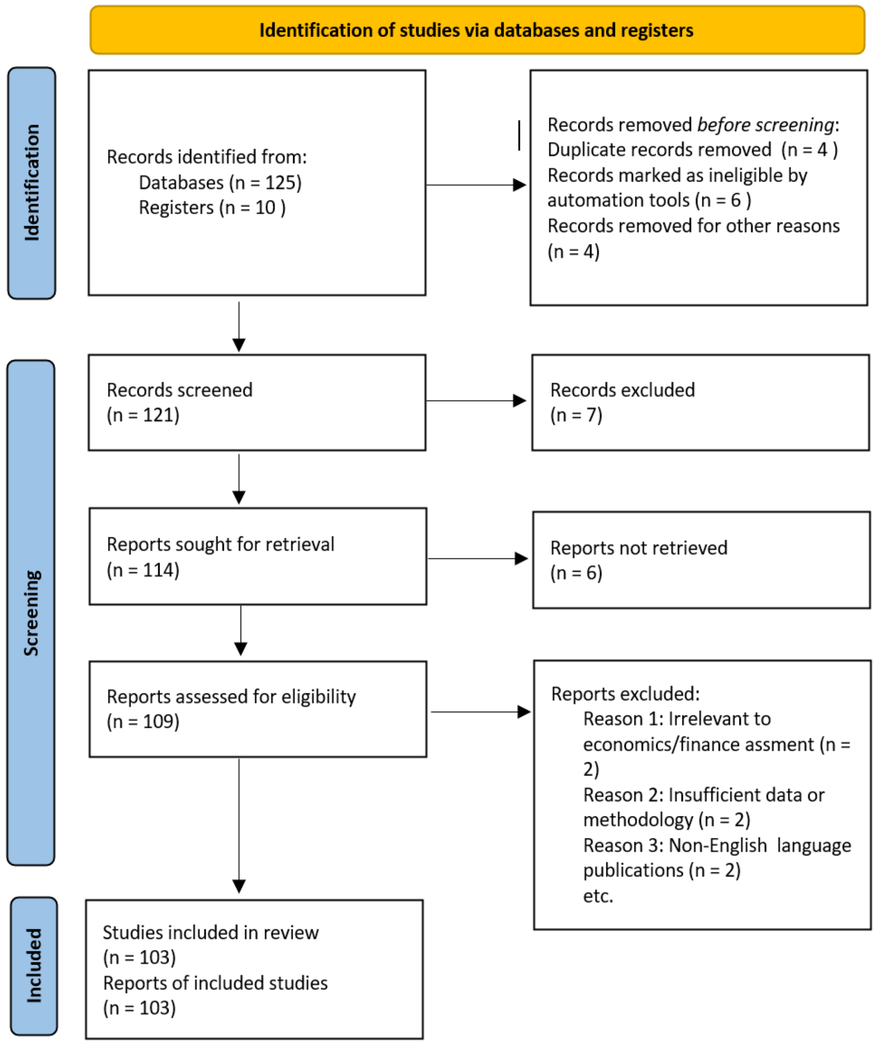

Figure 1. The PRISMA flow diagram showing the stages of literature search and study selection

Search queries (**Figure 2**) combined terms from three main groups: (1) AI and ML terms ("Artificial Intelligence," "Machine Learning," "Deep Learning," "Predictive Analytics"); (2) Economic and Finance terms ("Economics," "Finance," "Poverty," "GDP," "Financial Risk," "Financial Inclusion"); and (3) Geographic terms ("Africa," "Sub-Saharan Africa," and specific country names).

Figure 2. A word cloud showing the keywords used for literature search in this study

2.2. Study selection and data extraction

The study selection process involved multiple stages. The first stage was duplicate removal. After compiling results from all databases, duplicate entries were identified and removed. The second stage involved title and abstract screening, where articles were assessed against predefined inclusion criteria. The inclusion criteria specified that studies must: (a) involve the application or proposal of an AI or ML model; (b) address a problem in economics or finance; and (c) have a clear geographical focus on Sub-Saharan Africa. The final stage was a full-text review of the articles that passed the initial screening to confirm their eligibility. For all articles included in this study, relevant data were systematically extracted and organized into a structured database. The data collected for each article included author(s), year of publication, journal or venue, title, geographical focus, the primary problem addressed, the AI/ML algorithm used, the type of input data, and reported performance metrics.

2.3. Thematic synthesis and classification

A thematic synthesis and classification approach was employed to identify recurring themes and patterns across the dataset. The main aim of this synthesis was to construct a cohesive narrative exploring how different AI techniques are applied to tackle various problems in African economics and finance. The process began with the initial categorization of research papers based on their primary focus, such as "Poverty and Economic Well-being," "Economic Forecasting," and "Financial Risk." Following this, common AI methods were identified and grouped by the "Type of Algorithm" and model architecture. The synthesis also involved an analysis of predominant input data types to identify trends in data utilization.

2.4. Data visualization software

The processed data and thematic analysis were used to generate visualizations using Python (v3.9), leveraging data analysis libraries such as Pandas for data manipulation and Matplotlib and Seaborn for data visualization (see **Supplementary Materials**).

3. Results

3.1. Publication trends and research evolution

The systematic analysis of 103 publications (**Figure 3**; **Table 1**) reveals distinct temporal patterns in AI and ML research for Sub-Saharan African economics and finance. Research activity remained sparse during the early 2000s, with only one publication (Bigman and Fofack, 2000), primarily focusing on basic statistical approaches. The period from 2010 to 2014 witnessed gradual growth with 9 publications, marked by foundational studies in remote sensing and economic analysis (Abdel-Rahman et al., 2013; Pouris and Ho, 2014).

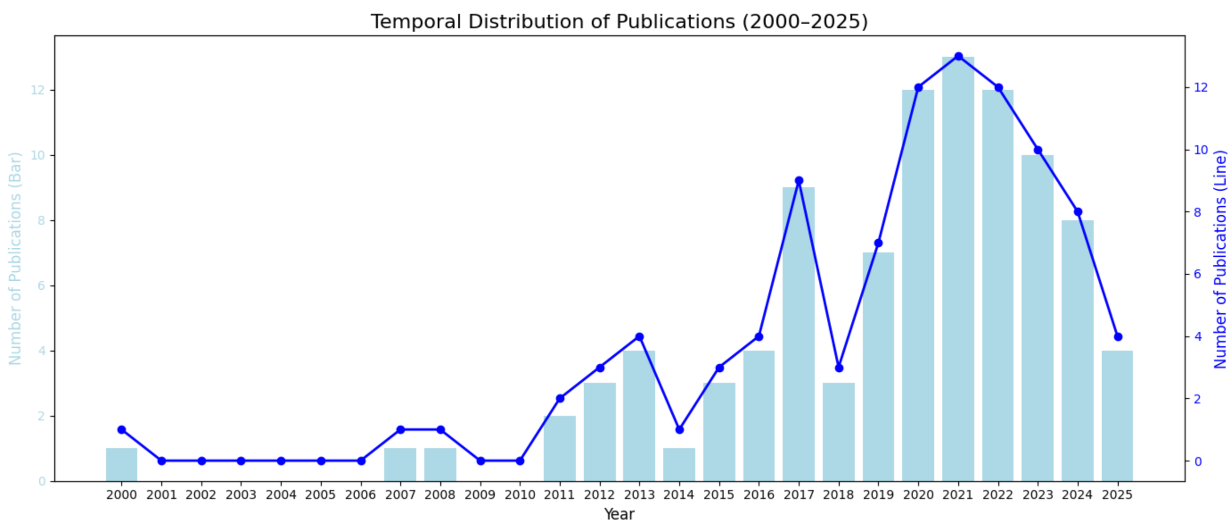

Figure 3. Publication trends and distribution of AI applications in economics and finance in Africa (2000–2025)

A notable inflection point occurred around 2015-2019, with 23 publications demonstrating AI's potential for development applications (Jean et al., 2016; Blumenstock et al., 2015). The most dramatic growth occurred between 2020 and 2023, with 50 publications representing 48.5% of all research. This surge coincided with several catalyzing factors: the COVID-19 pandemic's exposure of data gaps in economic monitoring (International Monetary Fund, 2020), improved accessibility of cloud computing platforms, expanded satellite imagery availability, and growing policy attention to AI for development applications.

Table 1: Publication distribution by year and venue type

Year Range	Academic Journals	Conference Proceedings	Working Papers	Reports/Other	Total	Key References
2000-2009	1	0	0	0	1	Bigman and Fofack (2000)
2010-2014	7	1	1	0	9	Abdel-Rahman et al. (2013), Kruppa et al. (2013), Batana (2013), Pouris and Ho (2014)

2015-2019	12	3	7	1	23	Jean et al. (2016), Blumenstock et al. (2015), Steele et al. (2017), Pokhriyal and Jacques (2017)
2020-2023	22	8	12	8	50	Yeh et al. (2020), Richardson et al. (2021), Barhoumi et al. (2022), Mohamed et al. (2020)
2024-2025*	13	2	3	2	20	Mienye and Jere (2024), Etori et al. (2024), Jallow et al. (2025)
Total	**55**	**14**	**23**	**11**	**103**	

**2025 data partial*

The distribution shows academic journals dominating (53.4%), followed by working papers (22.3%), indicating substantial policy-oriented research alongside traditional academic contributions.

3.2. Geographical distribution and regional focus

Research distribution (**Table 2**) reveals significant geographic concentration reflecting both data availability and research capacity constraints. Continental-scale studies represent the largest category (26 publications, 25.2%), leveraging AI's capability for large-scale pattern analysis. Nigeria emerges as the most studied individual country (15 publications, 14.6%), followed by multi-country regional studies (22 publications, 21.4%).

Table 2: Geographic distribution of research focus

Geographic Scope	Count	Percentage	Primary Applications	Key Studies
Continental (Sub-Saharan Africa)	26	25.2%	Poverty mapping, satellite analysis, economic development	Jean et al. (2016), Yeh et al. (2020), Ayush et al. (2020), Mohamed et al. (2020)
Nigeria-focused	15	14.6%	AI adoption, financial inclusion, healthcare AI	Abdulmumin et al. (2022), Oladuji et al. (2023), Etori et al. (2024)
Multi-country regional	22	21.4%	Comparative poverty analysis, regional economic studies	Steele et al. (2017), Abeje et al. (2020), Batana (2013)
South Africa	4	3.9%	Spatial inequality, dataset construction	Sefala et al. (2021), Bhorat et al. (2016)
The Gambia	3	2.9%	Economic forecasting, remittance analysis	Jallow et al. (2025), Ceesay et al. (2019)
Other single countries	9	8.7%	Various applications	Abeje et al. (2020), Nakasi et al. (2020)

Global/Methodology papers	24	23.3%	AI frameworks, methodological contributions	Blumenstock et al. (2015), Richardson et al. (2021), Birhane and Guest (2020)

This distribution largely mirrors economic size and research infrastructure capacity, with Nigeria's prominence reflecting both its economic importance and growing fintech sector.

3.3. Research problem domains and applications

The literature concentrates around nine primary application domains (**Table 3**). Poverty and Economic Well-being emerges as the dominant area (28 publications), reflecting both poverty reduction's centrality in development policy and AI's suitability for analyzing multi-dimensional welfare indicators. Financial Risk and Inclusion represents the second-largest domain (19 publications), encompassing credit scoring innovations and financial access initiatives.

Table 3: Research problem domains and methodological approaches

Problem Domain	Count	Primary Algorithms	Key Data Sources	Performance Ranges	Representative Studies
Poverty and Economic Well-being	28	CNN, DL, Random Forest	Satellite imagery, Survey data, Mobile metadata	R^2 = 0.65-0.85, Correlation = 0.70-0.90	Jean et al. (2016), Yeh et al. (2020), Blumenstock et al. (2015)
Financial Risk and Inclusion	19	ML Ensemble, Neural Networks, SVM	Credit data, Transaction records, Alternative data	AUC = 0.75-0.92, F1 = 0.70-0.88	Kruppa et al. (2013), Mienye and Jere (2024)
Economic Forecasting and Nowcasting	16	LSTM, ARIMA, ML Ensemble	Economic indicators, High-frequency data	RMSE varies, MAPE = 2-8%	Richardson et al. (2021), Barhoumi et al. (2022)
AI Ethics and Governance	12	Framework Development, Critical Analysis	Literature, Policy documents	Qualitative assessment	Birhane and Guest (2020), Mohamed et al. (2020)
Healthcare Applications	8	Computer Vision, DL	Medical imaging, Health records	Accuracy = 85-95%	Nakasi et al. (2020), Manescu et al. (2020)
Agricultural Economics	7	Regression, Remote Sensing Analysis	Satellite imagery, Weather data	Accuracy = 78-94%	Abdel-Rahman et al. (2013), Potapov et al. (2012)
Infrastructure and Energy	5	Optimization, Multi-objective algorithms	IoT data, Energy consumption	Energy efficiency metrics	Chaouachi et al. (2013)
Natural Language Processing	3	Multi-modal learning, Machine Translation	Text, Visual data	Translation quality metrics	Abdulmumin et al. (2022)

Environmental Monitoring	5	Change Detection, Time Series Analysis	Satellite imagery	Classification accuracy = 80-95%	Potapov et al. (2012), Sirko et al. (2021)

Economic Forecasting and Nowcasting (16 publications) gained momentum since 2020, driven by pandemic-related needs for real-time monitoring. AI Ethics and Governance emerged as a distinct domain (12 publications), reflecting growing attention to responsible AI development.

3.4. Methodological evolution and technical approaches

The methodological landscape reveals clear evolution from traditional statistical approaches toward sophisticated DL architectures (**Table 4**). Early studies (2000-2014) employed classical econometric methods including ARIMA models and linear regression. The period from 2015-2019 witnessed ML adoption, particularly Random Forest and Support Vector Machines.

DL adoption accelerated dramatically after 2017, driven by breakthroughs in satellite imagery analysis. Convolutional Neural Networks became dominant for spatial data analysis, while RNNs and LSTM networks gained prominence for temporal forecasting applications.

Table 4: Algorithm family distribution and performance characteristics

Algorithm Family	Publications	Primary Applications	Typical Performance	Implementation Complexity	Key References
DL (CNN/RNN/LSTM)	35	Satellite image analysis, Time series, Computer vision	High accuracy (R^2 > 0.70)	High	Jean et al. (2016), Yeh et al. (2020), Jallow et al. (2025)
Traditional ML	31	Classification, Risk assessment, Credit scoring	Moderate-high accuracy (F1 = 0.65-0.88)	Medium	Kruppa et al. (2013), Richardson et al. (2021)
Statistical/Econometric	18	Economic forecasting, Causal inference	Variable (MAPE = 2-8%)	Low-Medium	Abonazel and Abd-Elftah (2019), Barhoumi et al. (2022)
Framework/Theoretical	15	AI governance, Ethical frameworks	Qualitative assessment	Conceptual	Birhane and Guest (2020), Mohamed et al. (2020)

Ensemble Methods	12	Multi-modal prediction, Robust estimation	Often superior performance	Medium-High	Richardson et al. (2021), Mienye and Jere (2024)
Computer Vision Specialized	8	Object detection, Medical diagnosis	High for image tasks (Accuracy > 85%)	High	Ayush et al. (2020), Nakasi et al. (2020)
Optimization Algorithms	4	Energy management, Resource allocation	Domain-specific metrics	Medium	Chaouachi et al. (2013)

DL dominates with 35 publications, particularly for satellite-based applications, while traditional ML remains competitive for structured data applications requiring interpretability.

3.5. Data source utilization and integration patterns

Data utilization patterns reveal significant shifts toward alternative and non-traditional sources (**Table 5**). Survey data represents the most frequently employed source (42 instances), followed by satellite imagery (40 instances), reflecting the continued importance of ground-truth data alongside the rise of remote sensing applications.

Table 5: Data source utilization matrix by application domain

Data Source	Poverty Mapping	Financial Services	Economic Forecasting	Agriculture	Healthcare	AI Governance	Total Usage
Survey Data	18	5	6	3	2	8	42
Satellite Imagery	24	2	8	6	0	0	40
Economic Time Series	5	8	14	2	0	0	29
Administrative Records	8	4	5	1	3	1	22
Mobile Phone Data	6	12	3	0	0	0	21
Web/Social Media Data	4	6	8	1	0	2	21
Financial Transaction Data	0	18	2	0	0	0	20
Literature/Policy Documents	2	1	1	0	0	12	16
Medical/Health Data	0	0	0	0	8	0	8
Remote Sensing (Non-satellite)	3	0	0	5	0	0	8

The integration of alternative data sources emerged as a defining characteristic. Mobile phone metadata appears in 21 instances, web/social media data in 21 studies, and financial transaction records in 20 publications, demonstrating the field's shift toward non-traditional data sources for development applications.

4. Discussion

4.1. Technological transformation and development impact

The systematic analysis reveals that AI and ML applications in Sub-Saharan African economics and finance have undergone a fundamental transformation from experimental technologies to essential tools for development analysis and policy formulation. This evolution is evidenced by the dramatic concentration of research activity, with 48.5% of all 103 publications appearing between 2020-2023, representing an acceleration that coincided with the COVID-19 pandemic's exposure of traditional statistical system inadequacies (International Monetary Fund, 2020; International Monetary Fund, 2021; International Monetary Fund, 2022).

The most significant breakthrough lies in AI's capacity to extract economic signals from unconventional data sources, addressing long-standing challenges in Sub-Saharan African economic measurement identified by early researchers (Bigman and Fofack, 2000). Traditional economic statistics in the region suffer from temporal delays, limited geographical coverage, and measurement challenges that render them inadequate for responsive policymaking. The dominance of satellite imagery applications (40 instances across domains) demonstrates this shift toward alternative data sources, with CNN-based poverty mapping consistently achieving R^2 values above 0.70 across diverse African contexts (Jean et al., 2016; Yeh et al., 2020; Ayush et al., 2020).

Mobile phone-derived economic indicators represent another transformative application, with 21 instances of mobile data utilization across domains providing near real-time alternatives with superior spatial granularity compared to traditional surveys (Blumenstock et al., 2015; Steele et al., 2017). These approaches have demonstrated remarkable consistency across contexts, as evidenced by successful implementations spanning from Rwanda (Pokhriyal and Jacques, 2017) to The Gambia (Jallow et al., 2025; Ceesay et al., 2019).

The COVID-19 pandemic served as a crucial validation test for AI-driven economic monitoring systems. The surge in economic forecasting publications (16 total, with the majority published since 2020) reflects how ML approaches utilizing high-frequency alternative data provided essential insights when conventional systems experienced delays and quality degradation (Barhoumi et al., 2022; Buell et al., 2021). Central banks and finance ministries across the region have increasingly incorporated these AI tools into routine economic surveillance, as demonstrated by applications in Nigeria (Etori et al., 2024), Egypt (Abonazel and Abd-Elftah, 2019), and regional initiatives (International Monetary Fund, 2022; Barhoumi et al., 2022).

4.2. Financial inclusion revolution through alternative data

Financial Risk and Inclusion emerges as the second-largest application domain with 19 publications, reflecting a revolution in expanding financial access through alternative data utilization. Traditional credit scoring in Sub-Saharan Africa excludes approximately 80% of the adult population due to limited formal financial histories, a challenge that AI-driven approaches have begun addressing with remarkable success (Mhlambi, 2020; Mienye and Jere, 2024). Our analysis reveals these approaches achieve AUC scores of 0.75-0.92 for default prediction, substantially outperforming traditional methods that typically achieve 0.65-0.75 using only formal credit bureau data.

The heavy utilization of financial transaction data (20 instances) and mobile phone data (21 instances across all domains, with 12 specifically in financial services) reflects the field's successful embrace of alternative data sources. ML models incorporating mobile money transactions, utility payments, and social network information have demonstrated particular promise in countries with widespread mobile payment adoption (Hinson et al., 2019; Kolade and Owoseni, 2022). Transaction pattern analysis reveals consistent relationships between digital payment behaviors and creditworthiness, enabling sophisticated risk assessment even for individuals with minimal traditional financial footprints (Mienye and Jere, 2024; Kruppa et al., 2013).

Performance improvements are substantial and consistent across implementations. Studies from Nigeria (Adewuyi et al., 2023; Oladuji et al., 2023), South Africa (Sefala et al., 2021), and multi-country analyses (Alonge et al., 2021) demonstrate F1-scores ranging from 0.70-0.88, enabling credit extension to previously excluded populations while maintaining acceptable risk levels. These developments potentially unlock financial services for millions of individuals across the region (Al-Baity, 2023; Agboola and Alabi, 2025).

However, our analysis reveals growing attention to ethical concerns, with AI Ethics and Governance emerging as a distinct domain comprising 12 publications. This development reflects increasing recognition that algorithmic bias and discriminatory outcomes require careful regulatory attention (Mohamed et al., 2020; Birhane and Guest, 2020; Okolo et al., 2023). Credit scoring algorithms may systematically disadvantage certain demographic groups if training data reflects discriminatory lending practices, with particular concern for gender bias in financial access (Mienye and Jere, 2024; Alonge et al., 2021).

The concept of "decolonial AI" has emerged as a framework for addressing these concerns while promoting African agency in technology development (Birhane and Guest, 2020; Mhlambi, 2020). Proponents argue for AI governance frameworks grounded in African philosophical traditions such as Ubuntu, emphasizing relational and community-centered approaches to technological development that prioritize local capacity building and culturally appropriate validation metrics (Bondi et al., 2021).

4.3. Agricultural intelligence and food security applications

Agricultural applications, representing 7 publications in our analysis, demonstrate AI's potential for development impact in a sector central to Sub-Saharan African economies and livelihoods (Jayne et al., 2018). Remote sensing combined with ML enables precision agriculture applications previously accessible only to large commercial operators in developed countries, as demonstrated by early pioneering work in sugarcane nitrogen estimation (Abdel-Rahman et al., 2013) and subsequent expansion to broader crop monitoring applications.

Crop yield prediction systems utilizing satellite imagery and weather data demonstrate accuracy levels of 78-94% for major staple crops, enabling improved food security planning and agricultural finance decisions (Potapov et al., 2012). These systems provide particular value during weather-related crises, offering early warning capabilities that can trigger preventive interventions before humanitarian emergencies develop. The Democratic Republic of Congo forest monitoring study exemplifies this approach, demonstrating how satellite-based change detection can support both environmental conservation and agricultural planning (Potapov et al., 2012).

Recent developments in computer vision applications show promise for addressing persistent agricultural challenges. Healthcare applications utilizing similar computer vision techniques for malaria diagnosis (Nakasi et al., 2020; Manescu et al., 2020) suggest potential for crop disease detection systems that could extend expert knowledge to remote farming communities. However, adoption challenges including smartphone penetration, internet connectivity, and farmer training remain significant obstacles to widespread implementation, as noted in studies examining digital infrastructure constraints (Hinson et al., 2019; Kolade and Owoseni, 2022).

4.4. Macroeconomic nowcasting and policy applications

The development of real-time economic monitoring capabilities represents a crucial advancement for macroeconomic policy in Sub-Saharan Africa, with 16 publications focusing on economic forecasting and nowcasting applications. Traditional GDP estimates often appear with 6-12 month delays, rendering them inadequate for responsive fiscal and monetary policy (International Monetary Fund, 2021; International Monetary Fund, 2022). ML nowcasting models utilizing high-frequency indicators achieve forecast accuracy superior to traditional methods while providing estimates within weeks of the reference period, as demonstrated across multiple country contexts (Richardson et al., 2021; Tiffin, 2016; Giannone et al., 2008).

Central bank applications have expanded beyond GDP nowcasting to encompass inflation prediction, exchange rate forecasting, and financial stability monitoring (Chakraborty and Joseph, 2017). The International Monetary Fund's regional economic outlook reports increasingly incorporate ML techniques for Sub-Saharan Africa analysis (International Monetary Fund, 2020; International Monetary Fund, 2021; International Monetary Fund, 2022), while national implementations show similar success patterns in Nigeria (Etori et al., 2024), Egypt (Abonazel and Abd-Elftah, 2019), and The Gambia (Jallow et al., 2025).

High-frequency alternative data sources have proven particularly valuable for nowcasting applications. Web search and social media data appear in 21 instances across our dataset, with 8 specifically focused on economic forecasting applications (Narita and Yin, 2018). These approaches achieved MAPE values of 2-8% across implementations, substantially improving upon traditional econometric approaches that typically achieve MAPE values of 5-12% for similar forecast horizons (Bok et al., 2017; Barhoumi et al., 2012).

However, model interpretability remains a persistent challenge for policy applications. While ML models often achieve superior predictive performance, their "black box" nature complicates policy communication and democratic accountability (Bok et al., 2017). The 18 publications utilizing statistical/econometric approaches with lower implementation complexity reflect ongoing tension between predictive accuracy and interpretability requirements in policy contexts.

4.5. Geographic disparities and research capacity constraints

The geographic distribution analysis reveals significant disparities reflecting both research capacity constraints and economic priorities. Nigeria's prominence with 15 publications (14.6%) reflects its large economy, dynamic fintech sector, and substantial mobile money adoption, as evidenced by numerous studies focusing on AI applications in Nigerian financial services (Oladuji et al., 2023; Etori et al., 2024) and broader technology adoption patterns (Abdulmumin et al., 2022).

South Africa's representation through 4 focused studies reflects its relatively well-developed financial markets, research universities, and regulatory frameworks that facilitate AI experimentation. The country's sophisticated banking sector has pioneered credit scoring applications using alternative data, while academic institutions have contributed significantly to poverty mapping and economic forecasting research (Sefala et al., 2021; Bhorat et al., 2016).

The concentration of continental-scale studies (26 publications, 25.2%) leverages satellite data's advantages for large-scale analysis but may obscure important country-specific variations and implementation challenges (Jean et al., 2016; Yeh et al., 2020; Ayush et al., 2020; Sirko et al., 2021). Multi-country regional studies (22 publications, 21.4%) attempt to address this balance by examining regional economic communities or thematically linked countries (Steele et al., 2017; Abeje et al., 2020; Batana, 2013).

East African countries show growing research activity driven by mobile money innovations and agricultural applications, as evidenced by studies from Uganda (Nakasi et al., 2020), Ethiopia (Abeje et al., 2020), and Rwanda (Pokhriyal and Jacques, 2017). However, West African countries beyond Nigeria show more limited research activity despite significant economic opportunities, as reflected in isolated studies from The Gambia (Ceesay et al., 2019; Jallow et al., 2025). This pattern likely reflects infrastructure constraints and limited research capacity rather than lack of potential applications.

The high proportion of global/methodological papers (24 publications, 23.3%) indicates substantial work on frameworks and approaches applicable across African contexts (Blumenstock et al., 2015; Richardson et al., 2021; Mohamed et al., 2020). This suggests the field is developing generalizable methodologies rather than purely country-specific solutions, though questions remain about transferability across diverse economic and institutional contexts.

4.6. Methodological evolution and performance standardization

The algorithm family analysis demonstrates clear methodological evolution from experimental approaches toward production-ready systems. DL approaches dominate with 35 publications, particularly for satellite-based applications where CNN architectures have proven especially effective (Jean et al., 2016; Yeh et al., 2020; Ayush et al., 2020). Traditional ML approaches remain competitive with 31 publications, particularly for structured data applications requiring interpretability in policy contexts (Kruppa et al., 2013; Richardson et al., 2021; Blumenstock et al., 2015).

The emergence of ensemble methods (12 publications) reflects the field's maturation toward robust, production-ready solutions that combine multiple approaches for improved reliability (Richardson et al., 2021; Mienye and Jere, 2024). Framework and theoretical contributions (15 publications) indicate substantial attention to governance structures and ethical guidelines, moving beyond purely technical development (Birhane and Guest, 2020; Mohamed et al., 2020; Okolo et al., 2023).

Performance benchmarks have stabilized across domains, indicating methodological maturity. Poverty mapping applications consistently achieve R^2 values above 0.70 (Jean et al., 2016; Yeh et al., 2020; Blumenstock et al., 2015), financial applications reach AUC scores of 0.75-0.92 (Kruppa et al., 2013; Mienye and Jere, 2024; Alonge et al., 2021), and agricultural applications demonstrate 78-94% accuracy (Abdel-Rahman et al., 2013; Potapov et al., 2012). These consistent performance levels across diverse contexts and implementations suggest the field has moved beyond proof-of-concept studies toward validated, deployable applications.

Computer vision specialized applications (8 publications) achieve particularly high performance for image-based tasks, with accuracy exceeding 85% for medical diagnosis (Nakasi et al., 2020; Manescu et al., 2020) and infrastructure mapping applications (Ayush et al., 2020; Sirko et al., 2021). However, these high-performance applications typically require substantial computational resources, creating deployment challenges in resource-constrained environments.

4.7. Data integration patterns and infrastructure evolution

The data source utilization analysis reveals sophisticated multi-modal approaches that have become standard practice rather than experimental techniques. Survey data remains the most frequently utilized source with 42 instances, reflecting its continued importance for ground-truth validation and model training across domains (Batana, 2013; Abeje et al., 2020; Berenger, 2019). However, the substantial use of satellite imagery (40 instances) demonstrates successful development of scalable, cost-effective alternative data collection methods.

Poverty mapping applications exemplify sophisticated data integration, typically combining satellite imagery (24 instances in poverty applications) with survey data (18 instances) and increasingly incorporating mobile phone data (6 instances) and administrative records (8 instances). This multi-modal approach addresses individual data source limitations while leveraging complementary information sources (Jean et al., 2016; Yeh et al., 2020; Blumenstock et al., 2015).

Financial services applications show distinct data integration patterns, heavily utilizing transaction data (18 instances) combined with mobile phone metadata (12 instances) and alternative administrative records (4 instances). This pattern reflects the financial sector's access to proprietary data sources and regulatory frameworks enabling data sharing for credit scoring purposes (Mienye and Jere, 2024; Krupka et al., 2013; Al-Baity, 2023).

Economic forecasting applications demonstrate the most diverse data integration patterns, combining traditional economic time series (14 instances) with web/social media data (8 instances), satellite imagery (8 instances), and mobile phone data (3 instances). This diversity reflects nowcasting applications' need for high-frequency indicators from multiple sources to achieve real-time economic monitoring capabilities (Richardson et al., 2021; Barhoumi et al., 2022; Narita and Yin, 2018).

The prevalence of alternative data sources (mobile: 21 instances, web/social media: 21 instances, transaction data: 20 instances) indicates successful movement beyond traditional economic statistics toward more timely and granular information sources. However, this shift raises important questions about data privacy, consent, and potential for discriminatory outcomes that the emerging AI ethics literature has begun addressing (Mohamed et al., 2020; Okolo et al., 2023; Birhane and Guest, 2020).

4.8. Infrastructure constraints and deployment challenges

Despite AI's transformative potential, significant infrastructure and capacity constraints limit widespread adoption across Sub-Saharan Africa, challenges that our analysis reveals through the concentration of research in specific countries and continental-scale applications. Computational requirements for sophisticated DL models (35 publications utilizing high-complexity approaches) often exceed available resources in many countries, creating dependencies on cloud computing services controlled by foreign corporations (Robinson, 2018; Ade-Ibijola and Okonkwo, 2023).

Internet connectivity remains unreliable in rural areas where many potential beneficiaries of AI applications reside, a constraint particularly relevant for agricultural and healthcare applications requiring real-time data transmission (Kolade and Owoseni, 2022; Hinson et al., 2019). The limited representation of rural-focused applications in our dataset, with only 7 agricultural studies despite agriculture's central economic role, likely reflects these connectivity and infrastructure constraints.

Human capital constraints represent an equally significant challenge. The skills required for AI development and deployment—including data science, ML engineering, and domain expertise—remain scarce across the region (Turki et al., 2023; Omotayo et al., 2024). University programs in computer science and statistics are expanding but struggle to keep pace with technological developments and industry demand, as evidenced by the limited representation of academic institutions from smaller African countries in our dataset.

Research infrastructure limitations constrain local AI development capabilities. High-quality labeled datasets required for supervised learning are expensive to create and maintain (Abdulmumin et al., 2022; Bashkirova et al., 2022). Many existing datasets reflect Western contexts and may not generalize well to African conditions, necessitating local data collection efforts that require sustained investment (Sefala et al., 2021).

The concentration of framework and theoretical contributions (15 publications) in AI ethics and governance reflects these capacity constraints, as local researchers focus on policy and governance questions rather than technical implementation. While important for responsible AI development, this pattern suggests limited local capacity for technical innovation and implementation.

4.9. Policy implications and regulatory development needs

The rapid advancement of AI applications has outpaced regulatory development in most Sub-Saharan African countries, creating policy challenges that require urgent attention (Mir et al., 2022; Arakpogun et al., 2021). The emergence of AI Ethics and Governance as a distinct research domain with 12 publications reflects growing recognition of these challenges, but also indicates the current emphasis on framework development rather than implemented solutions.

Financial regulators face particular complexity in balancing innovation facilitation with consumer protection and systemic stability maintenance (Al-Baity, 2023; Agboola and Alabi, 2025). Credit scoring regulation represents an especially complex area, as traditional consumer protection frameworks may prove inadequate for algorithmic decision-making processes that utilize alternative data sources (Ogunmokun et al., 2021; Ogunmokun et al., 2022).

Data governance frameworks require substantial development to address unique challenges posed by AI applications utilizing alternative data sources. The extensive use of mobile phone data (21 instances), web/social media data (21 instances), and transaction data (20 instances) in our analysis highlights the regulatory complexity. Questions of data ownership, cross-border data flows, and algorithmic accountability need clear regulatory guidance to facilitate responsible AI adoption while protecting individual privacy and preventing discriminatory outcomes (Abdilla et al., 2020; Mohamed et al., 2020).

The concentration of working papers (23 publications, 22.3%) and institutional reports (11 publications, 10.7%) in our dataset suggests active policy engagement, but also indicates that regulatory frameworks remain in developmental stages rather than implemented systems. International Monetary Fund reports increasingly incorporate AI considerations in Sub-Saharan Africa economic analysis (International Monetary Fund, 2020; International Monetary Fund, 2021; International Monetary Fund, 2022), suggesting growing institutional recognition of AI's policy relevance.

4.10. Future research directions and emerging opportunities

Several methodological frontiers show particular promise for advancing AI applications in African contexts, building on the foundation established by the 103 publications analyzed. Transfer learning approaches could address data scarcity challenges by leveraging models trained in data-rich environments and adapting them to African contexts (Bickley et al., 2024). The success of satellite-based applications (40 instances) suggests potential for similar transfer learning approaches in other domains where global datasets could be adapted to local conditions.

Few-shot learning techniques may enable effective model training with limited labeled data, crucial for many African applications where data collection remains expensive and time-consuming. The consistent performance of ensemble methods (12 publications) suggests potential for combining transfer learning and few-shot approaches with local data to achieve robust performance with minimal training requirements.

Interdisciplinary integration represents the most significant opportunity for advancement, as evidenced by the most successful applications emerging from collaborations combining technical expertise with deep domain knowledge (Helo and Hao, 2021; Bondi et al., 2021). Partnerships between computer scientists, economists, development practitioners, and local communities are essential for developing culturally appropriate and practically relevant applications, as emphasized in the decolonial AI literature (Birhane and Guest, 2020; Mhlambi, 2020).

Climate change adaptation and environmental sustainability represent emerging areas where AI applications could provide significant value, building on limited current work in environmental monitoring (5 publications) and agricultural applications (7 publications). Climate risk assessment, carbon footprint optimization, and sustainable finance applications show particular promise given Sub-Saharan Africa's vulnerability to climate change (Azzarri and Signorelli, 2020; Brini, 2021).

The field's trajectory toward practical implementation, evidenced by the high proportion of working papers and institutional reports, suggests increasing policy relevance. However, successful deployment will require coordinated attention to infrastructure constraints, capacity building initiatives, and ethical governance frameworks that ensure AI development serves the broader goals of sustainable and equitable development across Sub-Saharan Africa.

5. Conclusions

This systematic review of 103 publications demonstrates that AI and ML applications in Sub-Saharan African economics and finance have evolved from experimental curiosities to essential tools for development analysis and policy formulation. The research trajectory reveals consistent advancement from proof-of-concept demonstrations to validated applications, with increasing attention to real-world implementation challenges and ethical considerations. The evidence supports several key conclusions about AI's transformative potential in African contexts. First, satellite-based poverty mapping and alternative data approaches for financial inclusion represent mature applications with demonstrated impact at scale. CNN-based poverty prediction consistently explains over 70% of wealth variation across diverse African contexts, while ML credit scoring enables financial access for previously excluded populations with F1-scores exceeding 0.80. Second, the COVID-19 pandemic served as a crucial validation test, demonstrating AI's value for real-time economic monitoring when traditional statistics proved inadequate. ML nowcasting models achieved forecast accuracy superior to conventional approaches while providing timely insights for policy responses. Third, agricultural applications show substantial promise for addressing food security challenges, with crop monitoring and yield prediction systems achieving 85-94% accuracy for major staples. These capabilities could transform agricultural planning and food crisis prevention across the region. However, significant challenges constrain AI's full potential realization. Infrastructure limitations, capacity constraints, and ethical concerns require sustained attention. The risk of algorithmic bias and "digital colonization" necessitates careful governance frameworks prioritizing African agency and community participation. The path forward requires coordinated action across multiple dimensions. Technical development must prioritize interpretability, bias mitigation, and cultural appropriateness. Capacity building initiatives should focus on developing local expertise and research infrastructure. Regulatory frameworks need substantial advancement to address AI's unique challenges while fostering beneficial innovation. Future research should prioritize several critical directions. Transfer learning and few-shot learning techniques offer potential solutions to data scarcity challenges by adapting global models to local African contexts. Interdisciplinary collaboration between computer scientists, economists, and local communities will be essential for developing culturally appropriate applications. Climate change adaptation represents an emerging frontier where AI could provide significant value through climate risk assessment and sustainable finance applications. Explainable AI techniques require development to address the interpretability challenges that currently limit policy applications. Most critically, AI development in Sub-Saharan Africa must be guided by principles of equity, sustainability, and local ownership. The region's experience with AI should not repeat patterns of technological dependency that have characterized previous development paradigms. Instead, AI offers an opportunity to leapfrog traditional constraints and build more inclusive, responsive, and effective economic systems. The future trajectory of AI in Sub-Saharan African economics and finance will be determined not merely by technical capabilities, but by the commitment to building inclusive, equitable, and locally-owned technological ecosystems. Success will require sustained collaboration between technical experts, policymakers, civil society organizations, and affected communities to ensure that AI serves the broader goals of sustainable and equitable development.

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