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Ai-Driven Currency Forecasting in Emerging African Economies: Risks of Algorithmic Dependence

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Abstract: Artificial Intelligence (AI) has become one of the defining technologies of the 21st century. Despite growing attention to AI applications in currency forecasting, there remains a scarcity of research on African contexts. Specifically, the risks of algorithmic dependence have been underexplored in the African financial policy literature, even as reliance on foreign-developed technologies accelerates. Therefore, this study sought to examine the risks of algorithmic dependence in AI-driven currency forecasting in emerging African nations. The study was grounded in dependency theory. In addition, the study relied on a convergent mixed-methods design. The study gathered secondary data and primary data from 60 key informant interviews (KIIs) with central bankers, fintech practitioners, analysts, and academics from four African nations (Kenya, Egypt, Nigeria, and South Africa). Four risks emerged as primary concerns: limited accountability (22/60; 36.7%), data bias and misrepresentation (16/60; 26.7%), erosion of institutional capacity (13/60; 21.7%), and geopolitical dependence (9/60; 15.0%). The findings revealed that algorithmic dependence is both a technical vulnerability and a socio-political phenomenon that reproduces external epistemic authority and geo-economic asymmetries. Therefore, this study concludes that the promise of AI-driven currency forecasting could turn into a new cycle of subordination in the global financial order if a context-sensitive AI adoption strategy is not implemented for currency forecasting in African states.

Keywords: Artificial Intelligence; Algorithmic Dependence; Risk; Currency Forecasting; Africa

1. Introduction

Artificial Intelligence (AI) has become one of the defining technologies of the 21st century. In the financial sector, AI applications are particularly transformative, reshaping areas such as credit scoring, fraud detection, portfolio management, and algorithmic trading. Among these applications, foreign-exchange markets stand out as a critical domain for AI deployment because of their size, volatility, and global interconnectedness. Within this domain, a

central application is currency forecasting. According to Zorzi and Rubaszek (2020), the term currency forecasting refers to the practice of predicting future movements in exchange rates between currencies. It combines economic theory, statistical methods, and increasingly machine-learning techniques to produce predictions of exchange rate movement over specified horizons (intraday, daily, weekly, monthly, or longer). Ayitey Junior et al. (2023) aver that common AI tools in currency forecasting include Artificial Neural Networks



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(ANNs) and long short-term memory (LSTM).

AI is revolutionizing currency forecasting by facilitating models that consider both historical and macroeconomic data as well as high-frequency market data to provide near-real-time exchange rate predictions (Abir et al., 2024). The essence of the ongoing use of AI in currency predictions is the assurance of increased accuracy, efficiency, and flexibility in addressing financial uncertainty. Empirical studies suggest that these AI techniques outperform classical econometric approaches in volatile conditions (Abir et al., 2024). Alaminos et al. (2021) further reported that deep neural networks, decision-tree ensembles (random forests and extreme gradient boosting), and deep belief networks yielded higher predictive precision than conventional statistical approaches for currency-crisis prediction. Nonetheless, these performance gains tend to be context-dependent.

Despite these advantages, the diffusion of AI in currency forecasting raises critical risks. A central concern is algorithmic dependence. In the context of this study, the terms “algorithmic dependence” denote the excessive reliance on computational or automated systems of decision making whose training data, assumptions, and failure modes may be poorly understood by local policymakers. Algorithmic dependence is of particular concern in emerging economies, where data limitations, infrastructural constraints, and weaker regulatory capacity can undermine model reliability and institutional control (Alper & Miktus, 2019). Studies of advanced markets and BRICS nations demonstrate that AI improves currency forecasting performance (Abir et al., 2024). However, models developed in and calibrated to developed markets do not transfer seamlessly to contexts marked by different structural drivers, market microstructure, and data availability (Islam et al., 2020; Alaminos et al., 2021).

African emerging nations exemplify both the promise and the perils of AI-driven currency forecasting. “Emerging nations” denote countries that are continually making positive strides to improve their economies. According to Lui-Wai (2017), these countries exhibit i) a drive to modernization, ii) a high global connectivity, iii) increasing domestic strength in terms of institutional and infrastructural development, and iv) a high level of stability. Many

African economies exhibit elevated exchange-rate volatility driven by commodity dependence, limited export diversification, speculative capital flows, and susceptibility to external shocks (UNCTAD, 2025). Therefore, more accurate currency forecasting tools could deliver significant benefits such as early-warning signals for central banks, improved corporate risk management, and better-informed investment decisions.

However, algorithmic dependence looms large in African contexts. African economies often lack the data infrastructure needed to train robust AI models. Africa holds under 1% of global data-centre capacity (Xalam, 2024). This limited local hosting forces reliance on overseas cloud regions and providers for storage and large-scale model training. In addition, many central banks and financial actors rely on algorithms developed by foreign firms and imported models that have been trained on data from fundamentally different economies.

According to Islam et al. (2020), there is sustained scholarly attention on AI-driven approaches (particularly, neural-network architectures) to currency forecasting. Despite growing attention to AI applications in currency forecasting, there remains a scarcity of research on African contexts. Most empirical studies focus on developed economies and or emerging markets outside Africa, like China, India, and Brazil. Where Africa is mentioned, the emphasis is often on fintech adoption broadly rather than on currency forecasting. Moreover, the risks of algorithmic dependence have been underexplored in the African financial policy literature, even as reliance on foreign-developed technologies accelerates. This gap is significant given the region’s heightened vulnerability to currency crises. Without critical analysis, there is a danger that African economies may adopt AI in ways that weaken rather than strengthen their financial systems.

This study examines the risks of algorithmic dependence in AI-driven currency forecasting within emerging African economies. Framing the study against the global landscape of AI adoption, this research contributes to the growing discourse on financial resilience in emerging markets. It highlights the specific challenges African economies face in leveraging AI while safeguarding autonomy.

2. Theoretical Framework

This study is grounded in dependency theory. The theory postulates that: (1) the world economy is organized into interacting “core” and “periphery” zones; (2) peripheral economies are integrated in subordinate roles; and (3) this structure generates persistent asymmetries—capital, technology, and surplus value flow toward the core, thereby producing external dependence (Hout, 2023). From the theory’s structuralist foundation, underdevelopment in the Global South is a structural condition produced by unequal relationships with the Global North. As per Kvangraven (2023), this pattern of dependency reinforces patterns of inequality and limits autonomous development.

According to Ellner (2024), dependency theory traces its intellectual lineage to mid-20th-century Latin American structuralists and Marxist scholars. Key proponents include scholars like Raúl Prebisch, Andre Gunder Frank, Fernando Henrique Cardoso, and Samir Amin. Since its inception, the theory has bifurcated into radical (delinking/ structural transformation) and reformist (state-led industrial policy within the world market) strands (Ellner, 2024). Contemporary scholarship neither treats dependency as doctrinaire fatalism nor as obsolete; instead, many authors adapt its tools to analyse financial subordination, unequal exchange, and global value-chain asymmetries. In addition, the theory encompasses technological dependence, as seen in scholarship on information and communication technologies (ICTs) and digital sovereignty (Mortier, 2025).

However, critics argue that the theory is overly deterministic and underplays domestic agency (Treacy, 2022). Nonetheless, dependency theory offers a pertinent theoretical frame for this study by highlighting asymmetric economic and technological relationships between developed “core” countries and peripheral African economies. It explains how external control of productive resources, technology, and knowledge (embodied in this study as foreign-developed AI forecasting tools) reproduces dependency. Through this lens, this study views algorithmic dependence as a modern mechanism of financial subordination where centre–periphery vulnerabilities are replicated. Therefore, framing AI adoption through

dependency theory i) clarifies structural risks, ii) informs governance priorities, and iii) underlines why technological transfer without capacity-building exacerbates financial fragility in Africa’s emerging economies.

3. Methodology

This study adopted a convergent mixed-methods research design to examine the risks of algorithmic dependence in emerging African economies. The choice of mixed methods was justified by the need to capture the qualitative and quantitative aspects of the risks arising from dependence on AI in currency forecasting in African emerging economies. The study gathered primary data from 60 key informant interviews (KIIs) with key stakeholders from Kenya, Egypt, Nigeria, and South Africa. These four African nations offer data-rich contexts suited to studying algorithmic dependence, given their relatively higher digital-financial penetration and active fintech sectors with significant foreign-exchange exposure, compared to other African countries. The key informants were selected through purposive sampling. These informants included policymakers in central banks, fintech innovators, financial analysts, and academic experts in African monetary policy. The KIIs were conducted between February and June 2025 via video calls using a semi-structured guide covering perceived risks; interviews averaged 45 minutes, were audio-recorded with consent, and transcribed verbatim. In addition, document analysis of books, journals, policy papers, fintech reports, and regional AI strategies supplemented the KIIs. The gathered data were analysed using content analysis. The Findings from the quantitative and qualitative strands were integrated at the interpretation stage through triangulation.

4. Result and Discussion

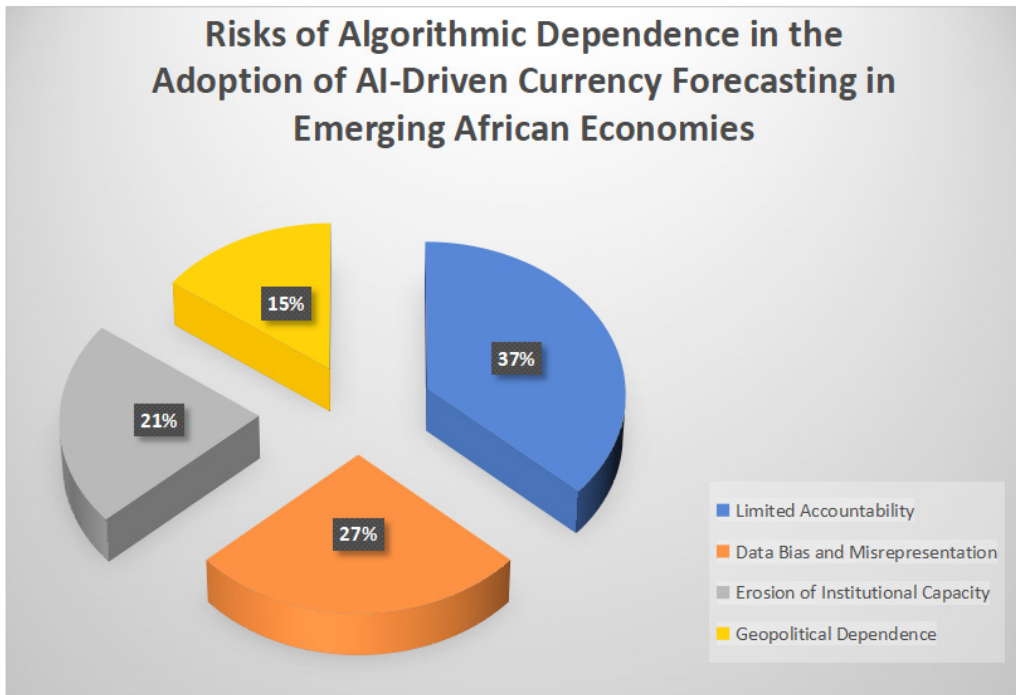
This section discusses four central risks of algorithmic dependence in the adoption of AI-driven currency forecasting in emerging African economies. These risks include limited accountability, data bias and misrepresentation, erosion of institutional capacity, and geopolitical dependence. **Table 1** below summarizes the prevalence of these risks, as per the study’s respondents.

Table 1: Risks of Algorithmic Dependence in the Adoption of AI-Driven Currency Forecasting in Emerging African Economies

Risk	Frequency (n = 60)	Percentage
Limited Accountability	22	36.7%
Data Bias and Misrepresentation	16	26.7%
Erosion of Institutional Capacity	13	21.7%
Geopolitical Dependence	9	15.0%
Total	60	100%

Table 1 above offers a clear picture of relative salience. Roughly one third of the study respondents (36.7%) identified limited accountability (opacity in models, procurement, and decision-making) as their chief concern. The next largest share (26.7% of the respondents) flagged data bias and misrepresentation stemming from imported models and non-representative training data. Further, 21.7% of the key informants recognized erosion of institutional capacity as a risk of algorithmic dependence. This substantial minority underscores fears about deskilling, vendor lock-in, and weakened governance. Finally, the remaining 15.0% of the key informants acknowledged that algorithmic

dependence results in the risk of geopolitical dependence. This signals a meaningful though smaller concern about jurisdictional exposure and external leverage. Viewed together, the top two categories (accountability and data bias) constitute 63.4% of primary concerns. This finding reveals that governance and empirical validity dominate stakeholder anxiety. Adding institutional erosion pushes the cumulative share to 85.1%. This highlights how governance, data, and capacity issues overwhelmingly shape perceptions of algorithmic dependence. The pie chart in **Figure 1** makes the differences in these proportions visually immediate.



4.1 Limited Accountability

Among the 60 key informants, 22 (36.7%) identified limited accountability as the principal risk of AI-driven currency forecasting. AI systems, particularly

deep learning models such as LSTM networks, often function as black boxes. Their outputs are generated through non-linear processes that are not easily interpretable. Unlike traditional econometric models,

where assumptions and coefficients can be explained, AI-based forecasts resist transparency. A central-bank official pointed out that;

AI-driven currency forecasting involves multilayered “black-box” complex models. These AI tools entail undocumented data provenance and hidden preprocessing or feature-engineering steps embedded in vendor pipelines (KII12, 2025)

The multidimensional opacity described in the excerpt above produces accountability gaps (whether technical, contractual, and institutional) that impede meaningful scrutiny and corrective action when forecasts fail. For African central banks, this opacity introduces a profound accountability dilemma. Policymakers are expected to justify decisions such as interest rate adjustments or foreign exchange interventions to legislatures, markets, and the public. Yet, when forecasts are derived from opaque AI systems, the rationale behind such decisions cannot be easily communicated. This erodes credibility and weakens the democratic accountability of financial institutions.

The problem is compounded by the limits of explainable AI (XAI). As De Bruijn et al. (2022) argue, even when technical explanations are offered, they often fail to produce legitimacy in practice. Explanations may be overly technical, contested, or perceived as self-serving, especially in policy domains where facts are ambiguous and values are contested. In these environments, even efforts to deliver XAI outputs can contribute minimally to recover confidence; rather, they run the risk of generating distrust or opposition when the populace perceives attempts to explain as incomprehensible jargon or as attempts to conceal incomprehensible decision-making.

This relationship can further increase the sense of elitism in African settings, where the level of institutional trust is low (Omeihe, 2023). Technical opacity is not merely a barrier to expert scrutiny; it also shapes how citizens perceive the legitimacy of monetary governance. By outsourcing interpretative authority to vendors and algorithms, African central banks risk creating the perception that critical policy tools are beyond domestic oversight. In effect, opacity does not just obscure technical processes; it actively reshapes the political economy of accountability by relocating responsibility away from domestic

institutions.

4.2 Data Bias and Misrepresentation

Most African financial institutions lack the infrastructure to develop large-scale forecasting models. This shortfall implies adopting AI tools created in the Global North. These models are typically trained on high-frequency, high-volume datasets from developed markets such as the U.S. dollar or Eurozone currencies. 16 of the 60 key informants (26.7%) identified that algorithmic dependence increases data bias and misrepresentation in African emerging economies. A key informant noted that

Currency forecasting tools procured from providers in advanced markets are typically trained on high-frequency, high-volume datasets (e.g., dollar–euro order books, deep liquidity series) that simply do not reflect the data environment of many African currencies (KII9, 2025).

Another central bank official added;

The vendor model ignored informal FX turnover. So its signal was consistently late (KII6, 2025).

A Fintech official also remarked that;

Global order-book data makes our remittance spikes invisible (KII34, 2025).

Based on the above quotations, algorithmic dependence has systematic bias and misrepresentation when used without careful adjustments. This is conceptually epistemic dependency: imported algorithms contain narratives and structural assumptions based on advanced-market microstructure. Some of the key informants observed that imposing these assumptions on African contexts distorts inference and policy directions (KII15, 2025; KII1, 2025; KII4, 2025; KII50, 2025; and KII39, 2025). Not only is it a problem of technical transfer (domain shift, concept drift, overfitting to foreign data), but it is also a structural reproduction of external epistemologies in which economic realities are made sense of with models that have been fitted to other institutions, instruments, and market behaviours. This epistemic inferiorization of African emerging economies through imported AI models is a pressing locus of decolonial critique. This preempts the necessity of context-specific AI development that will capture African economic systems.

The more African central banks and financial

institutions subscribe to a similar algorithmic forecasting system, typically through the same international suppliers, the more the region runs the risk of synchronized faulty decisions. In this sense, AI adoption in finance resembles the global financialization of the 2000s, where homogenous models contributed to systemic crises. The African context offers an early warning: without diversification and local adaptation, AI could reproduce similar cycles of herd-like fragility across the continent.

Relying on advanced AI models to address misrepresentation has its fair share of challenges. Scholars like Birhane (2021) warned that focusing narrowly on model-level debiasing overlooks how algorithmic systems reproduce historical injustices and power asymmetries embedded in datasets and institutional practices. This implies that imported forecasting models do more than mispredict. Instead, they privilege analytic logics and data regimes that marginalize locally salient phenomena (for example, informal markets, remittances, segmented on-/offshore rates). Birhane's (2021) critique counsels that technical fixes must be nested within institutional reform. Therefore, debiasing remains partial without addressing who defines datasets, who controls model provenance, and how marginalized economic activities are rendered visible.

4.3 Erosion of Institutional Capacity

13 of the 60 key informants (21.7%) identified erosion of institutional capacity as the principal risk associated with AI-driven currency forecasting in African emerging nations. By outsourcing forecasting functions to AI, central banks risk diminishing their internal capacity to critically evaluate, adapt, or contest currency predictions. This was aptly observed by a central bank official who noted that;

Procurement of turnkey, vendor-managed forecasting solutions often substitutes for, rather than complements, internal analytic capability. Over time, this substitution produces skill attrition that leaves monetary authorities unable to validate, adapt, or govern the very tools they depend upon (KII19, 2025).

Three linked dynamics emerged from the KIIs and document analysis: deskilling, institutional brittleness from knowledge concentration, and governance deficits and ineffective model-risk management.

First, deskilling through outsourcing. Several central-bank analysts and technical staff reported that vendor solutions arrive fully packaged (models, dashboards, and maintenance), thereby reducing incentives for in-house teams to develop model-building skills. An official from a central bank aptly noted that;

Our staff increasingly perform monitoring tasks rather than model development. Advanced analytical work is deferred to external providers. This narrowing of in-house roles both lowers organizational learning and increases turnover among staff seeking technical careers elsewhere (KII44, 2025).

The second mechanism through which algorithmic dependence leads to erosion of institutional capacity is the institutional brittleness from knowledge concentration. This study established that where AI expertise in currency forecasting exists, it is often concentrated in a few individuals or dependent on vendor personnel embedded through service contracts (KII41, 2025; KII7, 2025; KII15, 2025). Such concentration creates single points of failure. For example, when external contracts lapse or key staff leave, given the intensifying talent war (Wasi et al., 2025), the institution's capacity to diagnose model failures or to transition to alternative solutions is diminished. Several KIIs described procurement clauses that limit code access and knowledge transfer (KII10, 2025; KII5, 2025; KII41, 2025; KII7, 2025; KII15, 2025). Such restrictions to AI knowledge access reinforce vendor lock-in and make succession planning difficult.

Governance deficits and weak model-risk management are the third mechanism in the erosion of institutional capacity. A report by Araujo et al. (2025) observed that the problem of skills deficit is among the leading operational setbacks to the adoption of AI in the central banks of various countries around the world. The lack of adequate technical personnel means that central banks can not have adequate and effective model governance practices such as version control, reproducibility checks, independent validation, and stress testing. This dilutes the capacity of the institution to enforce contractual obligations or to seek remedial action where forecasts go wrong. As a consequence, policy teams can either blindly trust the outputs of unverified algorithms or neglect them, which negatively affect the consistency of decisions.

The implications are substantive. The three linkages described above create institutional passivity, where expertise resides more in external software providers than in domestic policymakers. This hollowing out of capacity transforms central banks into consumers of algorithmic outputs, thereby undermining their role as independent centers of judgment. This erosion aligns with dependency theory, which views technological reliance as a form of structural subordination (Mortier, 2025). However, the study extends this theory by highlighting both material dependence and cognitive dependence (the loss of intellectual sovereignty over economic modeling).

4.4 Geopolitical Dependence

Nine of the 60 key informants (15.0%) assigned geopolitical dependence as their primary concern. Although fewer interviewees flagged it as the single top risk, discussions with several key informants revealed that geopolitical dependence functions as a cross-cutting vulnerability that amplifies the other four risks (opacity, data bias, and capacity erosion) and has strategic consequences that extend well beyond technical performance (KII3, 2025; KII17, 2025; KII56, 2025; and KII49, 2025). At the core of geopolitical dependence is concentration. According to Wasi et al. (2025), major AI platforms and market-data vendors are concentrated in a handful of powerful countries and corporations. Consequently, control over model updates, feature releases, or paid-access data feeds is a vector for influence (whether through pricing, selective access, or technical constraints). Such scenarios arise, especially during periods of heightened geopolitical tension, as is the case between China, the US, and Europe (Colther et al., 2025). Put differently, dependence on these providers extends beyond economics into questions of sovereignty.

Birhane's (2020) critique of "algorithmic colonization" situates vendor concentration within a historical and political economy frame. Where traditional colonialism imposed external political control, algorithmic colonization describes how externally produced technologies (shaped by foreign values, objectives, and market incentives) are imported into the Global South with limited scrutiny, thereby crowding out locally appropriate solutions and perpetuating structural dependency. Applied to

AI forecasting, this dynamic means that imported algorithms do more than introduce technical risk: they can i) displace local epistemic authority, ii) impoverish the development of domestic analytic ecosystems, and iii) lock policy processes into externally defined logics.

Three implications follow. First implication is that, sovereignty of monetary decision-making is compromised when the supply of algorithmic inputs is constrained or externalized. Even in the absence of active interference, the mere reliance on vendor roadmaps and foreign computing influences the timing, scope, and interpretability of policy advice in the African emerging countries. The second implication is that resilience is anchored on external stability. Wasi et al. (2025) demonstrated that the external environment can disrupt access to vital models or data. This can result in the generation of operational risk, which is not reflected even in standard model-risk frameworks. The third implication is that the strategic competition intensifies the procurement decisions. Procurement decisions are non-neutral technical acquisitions but geopolitical alignments that have signaling effects and may implicate reciprocal commitments, as shown in (Wasi et al., 2025).

The geopolitical dependency discussion reveals that the process of adopting AI-driven forecasting makes Africa a component of the asymmetric power relationship where external powers acquire indirect control over the monetary policy of the emerging economies in Africa. This intensifies the topicality of discussions on digital sovereignty because the use of AI in Africa is at the intersection of technological conflicts between the world-systems. To policymakers, it highlights that an algorithmic dependence is a strategic weakness that necessitates coordination at the regional and continental levels. More so, by defining algorithmic dependence as a geo-economic problem, one redefines the priorities of policymakers. Rather than treating model procurement solely as a cost/benefit or technical procurement problem, African central banks must evaluate strategic exposure. For example, which vendors, hosting jurisdictions, and data sources create systemic leverage? Addressing such concerns demands legal, institutional, and regional policy tools to protect operational continuity and to preserve the autonomy and legitimacy of monetary governance in African emerging nations.

Conclusion

This study examined the risks of algorithmic dependence in AI-driven currency forecasting across four emerging African economies. The study found four main risks of algorithmic dependence: limited accountability, data bias and misrepresentation, erosion of institutional capacity, and geopolitical dependence. These risks demonstrate that AI-driven currency forecasting in African economies is a double-edged sword. AI-driven currency forecasting provides technical efficiency and simultaneously entrenches epistemic and geo-economic asymmetries that undermine the monetary autonomy of African states. Thus, this study concludes that the prospect of AI-based currency forecasting may become another round of subordination in the international financial system, provided there is the absence of a context-sensitive approach of AI adoption to currency forecasting in Africa.

This study, according to the dependency theory, shows that algorithmic technologies can displace the domestic epistemic power and shift the analytic rents into the hands of the external suppliers. This study brings together three key insights in predicting the four most common dangers of algorithmic dependence. First observation is that the issue of AI-opacity is related to the crisis of legitimacy within a low-trust political economy through this study. The second lesson is that the research re-creates algorithmic bias as an economic and not just a social and political issue in the Global South. Thirdly, this study highlights collective vulnerability, loss of epistemic knowledge, and geopolitical dependency as significant but underrated in the use of financial AI.

Recommendation

This study recommends the following to balance the benefits of AI-driven forecasting with the risks arising from algorithmic dependence;

Short Term Priorities

1. Hybrid Forecasting Models: Central banks in African emerging markets need to embrace hybrid currency forecasting models, which involve AI predictions with human supervision and standard econometric methods. This eliminates the possibility of overdependence and still has the ability to predict with AI. This is one of

the most immediately feasible recommendations since integrating AI forecasts with human judgment and traditional models requires minimal structural change. Implementation requires institutional guidelines and training staff to interpret AI outputs alongside established methods since Central banks already use econometric models, and AI tools are increasingly available.

2. Legal and Policy Frameworks for Algorithmic Transparency: The relevant ministries and parliaments in African emerging economies should come up with policies and laws that will either dictate or inform the transparency and accountability of algorithms. In the short term, establishing regulatory sandboxes and interim guidelines where AI tools are tested under monitored conditions is achievable without waiting for full legislation. Feasibility: Moderate to high, depending on political will. Medium-term measures include drafting comprehensive legislation that requires the disclosure of algorithmic decision-making processes.

Medium-Term Priorities

3. Capacity-Building in AI and Monetary Forecasting: African emerging states are supposed to invest in local data science, econometrics, as well as AI development skills. The African universities and the central banks ought to liaise to generate local forecasting models, which are specific to African economies. These capacity-building initiatives could be achieved through joint research projects, scholarship programs, and specialized training for central bank analysts. Such capacity-building programs will play a crucial role in addressing the challenge of skill shortages that hinder the adoption of AI.

4. Promoting Local AI Platforms and Partnerships: African emerging nations ought to emphasize the local or regional development of AI platforms in order to protect economic autonomy. The introduction of foreign currency forecasting systems should not be encouraged, but rather partnerships with local fintech companies. Fostering public-private partnerships (PPPs) will create sustainable ecosystems for indigenous AI innovation. Encouraging fintech collaboration and PPPs requires funding, incubation hubs, and innovation-friendly regulation. These prerequisites should be developed first through government-enabled seed funding and innovation grants, and regulations (Recommendation 2)

Long-Term

1. Regional Collaboration and Shared Infrastructure: African regional blocs (such as ECOWAS) ought to consolidate their resources to build common data infrastructures and AI tools to become less dependent on outside vendors. This initiative could involve creating regional data-sharing agreements and establishing of regional AI hubs that reduce dependence on external vendors and enable economies of scale. Feasibility: Low to moderate in the short term, higher in the long term. Regional integration initiatives like ECOWAS or SADC often face political and logistical challenges, making this the most difficult to achieve quickly.

Together, the recommendations above prioritize skills development, transparency, regional cooperation, hybrid modeling, and indigenous innovation. All these are achievable within short-, medium-, and long-term horizons. The recommendations provide a pragmatic roadmap for African economies to harness AI while avoiding the structural vulnerabilities of algorithmic dependence.

Reference

- [1] Abir, S. I., Al Shiam, S. A., Zakaria, R. M., Shimanto, A. H., Arefeen, S. S., Dolon, M. S. A., ... & Shoha, S. (2024). Use of AI-Powered Precision in Machine Learning Models for Real-Time Currency Exchange Rate Forecasting in BRICS Economies. *Journal of Economics, Finance and Accounting Studies*, 6(6), 66-83.
- [2] Alaminos, D., Peláez, J. I., Salas, M. B., & Fernández-Gámez, M. A. (2021). Sovereign debt and currency crises prediction models using machine learning techniques. *Symmetry*, 13(4), 652.
- [3] Alper, C. E., & Miktus, M. (2019). *Digital connectivity in sub-Saharan Africa: A comparative perspective* (IMF Working Paper No. 19/210). International Monetary Fund.
- [4] Araujo, D., Schmidt, R., Sirello, O., Tissot, B., Villarreal, R. (2025). Governance and implementation of artificial intelligence in central banks. Irving Fisher Committee on Central Bank Statistics (IFC)/ Bank for International Settlements (BIS), 18.
- [5] Ayitey Junior, M., Appiahene, P., Appiah, O., & Bombie, C. N. (2023). Forex market forecasting using machine learning: Systematic Literature Review and meta-analysis. *Journal of Big Data*, 10(1), 9.
- [6] Birhane, A. (2020). Algorithmic colonization of Africa. *SCRIPTed*, 17, 389.
- [7] Birhane, A. (2021). Algorithmic injustice: a relational ethics approach. *Patterns*, 2(2).
- [8] Colther, C., Doussoulin, J. P., & Tontini, G. (2025). Artificial Intelligence and Global Power Dynamics: Geopolitical Competition, Strategic Alliances, and the Future of AI Governance. *Strategic Alliances and the Future of AI Governance*.
- [9] De Bruijn, H., Warnier, M., & Janssen, M. (2022). The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making. *Government information quarterly*, 39(2), 101666.
- [10] Ellner, S. (2024). Dependency Theory and Its Revival in the Twenty-First Century. *Latin American Research Review*, 59(3), 744-757.
- [11] Hout, W. (2023). Dependency theory. In *Elgar Encyclopedia of Development* (pp. 162-166). Edward Elgar Publishing.
- [12] Islam, M. S., Hossain, E., Rahman, A., Hossain, M. S., & Andersson, K. (2020). A review of recent advancements in forex currency prediction. *Algorithms*, 13(8), 186.
- [13] Kvangraven, I. H. (2023). Dependency theory: strengths, weaknesses, and its relevance today. In *A modern guide to uneven economic development* (pp. 147-170). Edward Elgar Publishing.
- [14] Lui-Wai, L. (2017). Chapter 8 - The Five Groups of World Economies. In *Redefining Capitalism in Global Economic Development*. Academic Press, 177-200,
- [15] Mortier, S. (2025). "Artificial Intelligence and European Nations' Fundamental Interests: A Reading of Dependency Theory."
- [16] Omeihe, K. O. (2023). *Trust and Market Institutions in Africa*. Springer International Publishing AG.
- [17] Treacy, M. (2022). Dependency theory and the critique of neo-developmentalism in Latin America. *Latin American Perspectives*, 49(1), 218-236.

- [18] UNCTAD (2025). Africa's vulnerability to global shocks highlights need for stronger regional trade. UNCTAD. Retrieved from <https://unctad.org/news/africas-vulnerability-global-shocks-highlights-need-stronger-regional-trade>
- [19] Wasi, A. T., Eram, E. H., Mitu, S. A., & Ahsan, M. M. (2025). Generative AI as a Geopolitical Factor in Industry 5.0: Sovereignty, Access, and Control. *arXiv preprint arXiv:2508.00973*.
- [20] Xalam (2024). The State of the African Data Center. Retrieved from <https://xalamanalytics.com/africa-reports/africa-data-center-market-report>
- [21] Zorzi, M.C., & Rubaszek M (2020). "Exchange rate forecasting on a napkin." *Journal of International Money and Finance*, 104(C).