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THE INSTITUTIONAL PARADOX: WHY INNOVATION INPUTS FAIL TO PREDICT OUTCOMES IN ETHIOPIA

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ABSTRACT

Ethiopia's National Innovation System (NIS) exhibits a persistent gap between policy ambition and innovation outcomes, raising critical questions about the systemic drivers and constraints of innovation in low-income settings. This study investigates the dynamic, non-linear relationships among innovation inputs and outputs using a mixed-methods design that combines stakeholder insights with a machine learning–driven analysis of global panel data. Survey and interview data from 130 Ethiopian stakeholders—spanning government, academia, and industry—reveal systemic challenges: policy incoherence (72%), infrastructural deficits (64%), human capital shortages (80%), chronic R&D underfunding (88%), and weak collaboration (74%). Quantitatively, we train a Convolutional Long Short-Term Memory network with multi-head attention (ConvLSTM-Attention) on 12 years (2011–2022) of Global Innovation Index data from 105 countries. Model interpretability is ensured through SHapley Additive exPlanations (SHAP). The model achieves high predictive accuracy (R^2 = 0.89 for knowledge and technology outputs; R^2 = 0.85 for creative outputs) and reveals that Human Capital and Research and Business Sophistication are the strongest global predictors of innovation. Crucially, however, these inputs yield negligible or even negative marginal returns in contexts of low institutional quality—such as Ethiopia (GII Institutions score: 32.7). Infrastructure similarly shows a negative association with innovation in low-income countries, suggesting misallocation or underutilization without complementary institutional and market capabilities. These findings challenge linear, input-centric policy approaches and underscore that institutional reform must precede or accompany investments in education, R&D, and infrastructure. We propose a sequenced policy roadmap—centered on regulatory sandboxes, innovation finance mechanisms, and Triple Helix collaboration platforms—that aligns with Ethiopia's Growth and Transformation Plan II and the African Union's STISA-2024. The study contributes theoretically by demonstrating the conditional nature of innovation drivers, methodologically by pioneering interpretable deep learning for NIS analysis, and practically by offering context-sensitive, evidence-based policy guidance for Ethiopia and similar economies.

KEYWORDS: National Innovation System (NIS), Machine Learning, Innovation Policy, Institutional Quality, Ethiopia, SHAP.

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1. INTRODUCTION

In a strategic shift with significant implications for its innovation trajectory, Ethiopia formally joined the BRICS grouping in 2024, becoming the bloc's newest member and its second African participant after South Africa. This membership introduces a novel geopolitical and economic dimension to Ethiopia's innovation systems ambitions, offering unprecedented access to alternative financing mechanisms. National Innovation Systems (NIS) are critical engines of sustainable economic development, particularly in low-income countries striving to transition from resource-dependent to knowledge-based growth models (Lundvall, 2007; Freeman, 1987). In sub-Saharan Africa, Ethiopia has demonstrated growing ambition in this domain, launching successive science, technology, and innovation (STI) policies and aligning its Growth and Transformation Plans (GTP I and II) with long-term structural transformation goals. However, despite increased public investment in education, infrastructure, and research institutions, the country continues to exhibit a persistent gap between innovation inputs and measurable outputs—a phenomenon often described as "inputs without outcomes" (UNCTAD, 2020; Shkabatur, 2021).

This disconnects points to deeper systemic weaknesses that extend beyond mere underfunding. Stakeholders frequently cite policy incoherence, weak institutional capacity, fragmented academia–industry linkages, and infrastructural bottlenecks as key impediments to effective innovation translation (Gouldson, 2020; Mezid Nasir Keraga, 2023). While qualitative assessments highlight these challenges, there remains a lack of integrated, dynamic analyses that quantify how different components of the NIS interact over time and under varying institutional conditions. Traditional econometric approaches—such as panel regressions—often assume linearity and static relationships, potentially obscuring the complex, lagged, and non-linear dynamics inherent in innovation processes.

To address this gap, this study advances a context-sensitive, data-driven re-conceptualization of Ethiopia's NIS by integrating mixed-methods analysis with a novel machine learning architecture: Convolutional Long Short-Term Memory networks with multi-head attention (ConvLSTM-Attention). Trained on 12 years (2011–2022) of panel data from 105 countries—including Ethiopia—the model captures temporal dependencies, interaction effects, and differential response lags across innovation drivers. Interpretability is achieved through SHapley Additive exPlanations (SHAP), enabling transparent identification of marginal contributions and threshold effects.

The central argument advanced in this paper is that institutional quality functions not merely as an independent determinant but as a systemic enabler—a force multiplier that modulates the returns on human capital, infrastructure, and financial investments. Without adequate governance, regulatory coherence, and implementation capacity, even well-designed policies risk yielding diminishing innovation returns. This insight reframes conventional input-centric strategies and calls for sequenced reforms prioritizing institutional strengthening as a prerequisite for effective resource deployment.

Theoretical, methodological, and practical contributions are threefold. First, the study refines NIS theory for developing economies by empirically demonstrating the conditional nature of innovation drivers. Second, it pioneers the application of ConvLSTM-Attention with SHAP interpretability to cross-national panel data, offering a replicable framework for policy simulation in data-scarce environments. Third, it translates findings into a phased, evidence-based policy roadmap tailored to Ethiopia's institutional reality, with implications for other African nations navigating similar development trajectories.

1.1. Theoretical Framework and Research Gap

National Innovation Systems (NIS) are not mechanical input–output machines but complex adaptive systems shaped by institutional context, temporal lags, and non-linear interactions among actors (Edler & Fagerberg, 2017; Lundvall, 2007). While foundational theories by Freeman (1987) and Lundvall (1992) established the NIS as a network of institutions that collectively generate, diffuse, and utilize knowledge, their empirical operationalization—particularly in low-income settings—has often relied on linear, static econometric models that fail to capture these dynamics. This study addresses this disconnect by proposing an integrated conceptual and computational framework that explicitly models innovation as a context-contingent, time-dependent, and non-linear process.

1.2. Conceptual Model

Building on the Global Innovation Index (GII) architecture and empirical insights from Ethiopia's policy landscape (UNCTAD, 2020; Shkabatur, 2021), we formalize the NIS as a dynamic system in which five core inputs—Institutions, Human Capital &

Research, Infrastructure, Market Sophistication, and Business Sophistication—jointly determine two innovation outputs: Knowledge & Technology Outputs (e.g., patents, R&D, high-tech exports) and Creative Outputs (e.g., design, media, digital services). These outputs, in turn, contribute to economic growth, proxied by GDP per capita.

Critically, this relationship is moderated by contextual factors—notably institutional quality and income level—that shape the marginal returns to innovation inputs. As illustrated in Figure 1, the system is not linear: the same investment in human capital may yield high returns in a high-governance environment but negligible or even negative outcomes where policy instability, weak IP enforcement, or bureaucratic fragmentation prevail.

To empirically capture these complex, context-dependent dynamics outlined in our conceptual model, this work translates framework into a formal mathematical structure. Rather than relying on traditional static, linear assumptions, we define a time-lagged, non-linear mapping. This formulation explicitly accounts for both the delayed effects of innovation inputs and the moderating role of institutional environments.

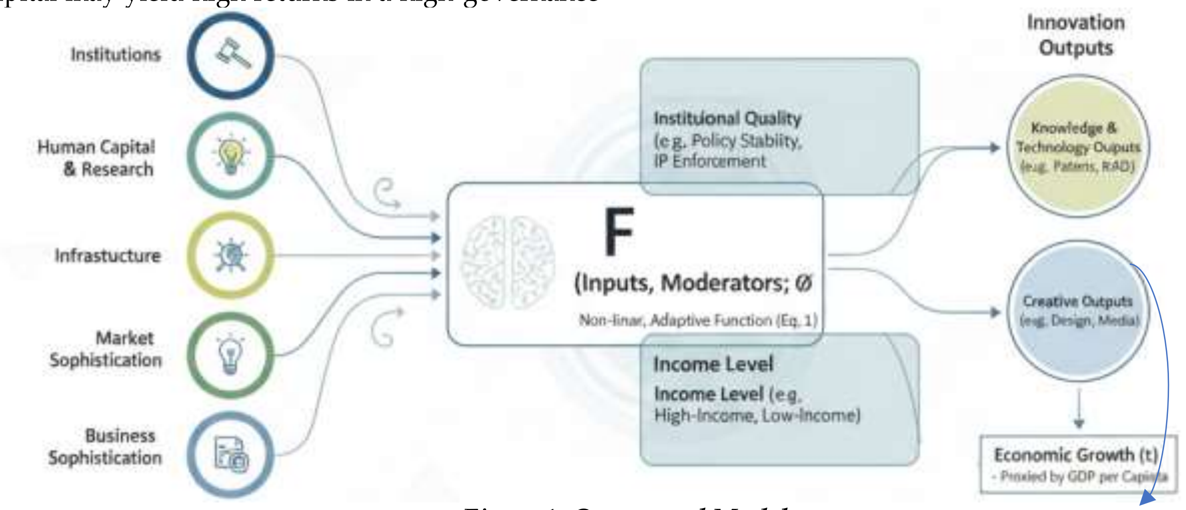

Figure 1: Conceptual Model.

Mathematically, we represent this system as a time-lagged, non-linear mapping:

$$Y_t = f(X_{t-\tau}, Z_t; \theta) + \epsilon_t \quad \text{Eq. 1}$$

where:

$Y_t \in R^2$ is the vector of innovation outputs at time t,

$X_t \in R^5$ denotes the five innovation inputs observed at lagged time steps $\tau = 1, \dots, L$,

Z_t represents contextual moderators (e.g., institutional quality, income group),

$f(\cdot)$ is a non-linear, learnable function capturing interactions and thresholds,

$\boldsymbol{\theta}$ are model parameters, and

ϵ_t is an error term.

This formulation departs from conventional panel regressions by allowing $f(\cdot)$ to be data-driven, adaptive, and capable of learning optimal lag structures and interaction effects—features essential for modeling innovation in volatile, institutionally fragile settings like Ethiopia.

Existing empirical studies on NIS in Africa—including Ethiopia—suffer from three interrelated limitations. First, methodological linearity: most analyses employ fixed-effects or OLS models that assume additive, linear relationships (e.g., Baris, 2019; Li et al., 2023). These approaches cannot detect threshold effects—such as the point at which infrastructure investment becomes productive—or interaction effects, like the conditional impact of human capital on innovation given institutional quality.

Second, temporal rigidity: Conventional models impose fixed lag structures or ignore lags altogether, despite strong theoretical and empirical evidence that innovation outcomes manifest over multi-year horizons (Griliches, 1979; Falk, 2012). This obscures the delayed impact of policy reforms or R&D investments.

Third, contextual blindness: Many studies treat NIS determinants as universal, neglecting how their efficacy varies by institutional and economic context. For instance, while human capital is consistently ranked as important globally, its impact in Ethiopia—where institutional quality (GII score: 32.7) is among the lowest—remains unquantified and poorly understood.

1.3. Research Gap and Contribution

This study bridges the methodological and

theoretical gap by introducing a dynamic, interpretable machine learning framework—ConvLSTM with attention and SHAP explanations—that explicitly models:

- Longitudinal dependencies across innovation trajectories,
- Non-linear and interactive effects among system components,
- Differential response lags (e.g., education reforms taking 5–10 years to affect output),
- Country-specific pathways through entity-aware modeling.

By training on global panel data (105 countries, 2011–2022) and applying SHAP values to interpret feature contributions, the model identifies which drivers matter most, when they matter, and under what institutional conditions. This enables a shift from generic policy prescriptions to context-sensitive, sequenced reform strategies—an advancement particularly relevant for latecomer economies like Ethiopia.

Thus, our theoretical contribution lies in operationalizing the NIS as a dynamic, moderated system, while our methodological innovation demonstrates how deep learning can enhance policy-relevant social science research without sacrificing transparency.

2. METHODOLOGY

This study adopts a sequential mixed-methods research design, integrating qualitative insights with quantitative predictive modeling to develop a context-sensitive understanding of Ethiopia's National Innovation System (NIS). The rationale for this approach lies in the dual nature of the research problem: while expert perceptions reveal structural bottlenecks and policy gaps, only longitudinal, data-driven analysis can uncover dynamic, non-linear relationships among innovation drivers. By triangulating stakeholder views with machine learning–based forecasting, the methodology ensures both ecological validity and analytical rigor (Creswell & Plano Clark, 2017).

2.1. *Qualitative Inquiry*

To ground the quantitative analysis in local realities, semi-structured interviews were conducted with 130 purposively selected key informants representing government agencies, research institutions, private enterprises, and international development partners. Participants were chosen based on their direct involvement in science, technology, and innovation (STI) policy formulation or implementation, ensuring domain expertise and strategic insight.

The interview guide explored five core dimensions of the NIS: (1) policy coherence and regulatory environment, (2) institutional capacity and coordination, (3) human capital development, (4) infrastructure and digital access, and (5) financing mechanisms and private-sector engagement. Data were thematically analyzed using a deductive coding framework aligned with the Global Innovation Index (GII) pillars (Dutta et al., 2023), supplemented by inductive codes emerging from responses.

Secondary qualitative data were drawn from national policy documents including UNCTAD Science, Technology and Innovation Policy Review (UNCTAD, 2020), to assess alignment between stated goals and systemic constraints.

2.2. *Quantitative Analysis*

The quantitative component employs a deep learning framework—Convolutional Long Short-Term Memory network with multi-head attention (ConvLSTM-Attention)—to model the temporal evolution of innovation outputs across countries, with a focus on Ethiopia's trajectory within a global comparative context.

The model is trained on 12 years (2011–2022) of panel data from 105 countries, drawn from two authoritative sources: (1) the Global Innovation Index (GII), which provides standardized metrics across 81 indicators grouped into seven pillars (WIPO, 2023); and (2) the World Bank's World Development Indicators (WDI), used for macroeconomic controls. Ethiopia is included as a focal case within this global sample, enabling both within-country trajectory analysis and cross-national benchmarking.

Table 1: Definition of Innovation Output Variables and Sub-Indicators.

Variable Category	GII Pillar	Sub-Pillars	Key Constituent Indicators (Examples)
Innovation Outputs	**Knowledge & Technology Outputs**	Knowledge Creation	Patent applications (PCT/resident) Scientific and technical publications Utility models by origin
		Knowledge Impact	Growth rate of GDP per person engaged New business density ISO 9001 quality certificates

		Knowledge Diffusion	High-tech exports (% of total trade) ICT services exports Intellectual property receipts
	Creative Outputs	Intangible Assets	Trademark application class count Global brand value Industrial designs by origin
		Creative Goods & Services	Creative goods exports Cultural and creative services exports National feature films produced
		Online Creativity	Mobile app creation Wikipedia edits Generic and country-code top-level domains (TLDs)
Innovation Inputs	**Institutions**	Political, Regulatory, & Business Environment	Political stability and safety Rule of law & Ease of starting a business
	Human Capital & Research	Education & R&D	Expenditure on education Government funding per pupil R&D expenditure (% of GDP)
	Infrastructure	ICT, Energy, & Logistics	ICT access and use Electricity output (kWh/cap) Logistics performance
	Market Sophistication	Credit & Investment	Credit to private sector Microfinance gross loans Venture capital deals
	Business Sophistication	Knowledge Workers & Links	GERD financed by business University-industry research collaboration

Source: Adapted from Global Innovation Index (WIPO, 2023).

While the GII provides one of the most comprehensive cross-national STI datasets, it has been critiqued for potential urban and formal-sector bias (Bogliacino et al., 2020). To mitigate this limitation, qualitative findings were used to contextualize results, particularly regarding informal innovation practices not captured by GII metrics.

Preprocessing and Imputation Strategy: Missing values—common in low-income country reporting—were imputed using K-Nearest Neighbors (KNN) with a temporal neighborhood window (k=3), following Jerez et al. (2010). This approach preserves country-specific time-series structure by imputing each missing observation using the three chronologically closest available years from the same country, thereby avoiding cross-sectional smoothing that could distort national innovation pathways. We employed the Fisher-type Augmented Dickey-Fuller (Fisher-ADF) panel unit root test (Maddala and Wu 1999), which is robust to unbalanced panels and heterogeneous dynamics. The test yielded a statistic with a p-value of 0.0001 for all input and output variables, leading to the strong rejection of the null hypothesis of non-stationarity. Consequently, all variables were confirmed to be stationary at levels I(0). Based on this result, the machine learning model was trained on the normalized index values without the need for differencing, preserving the original magnitude of the innovation indicators. and scaled to [0,1] using MinMax normalization to align with LSTM activation functions.

Model **Architecture:** Traditional econometric models such as Panel OLS assume linearity, additivity, and fixed lag structures—assumptions inconsistent with the complex, adaptive nature of innovation systems (Edler & Fagerberg, 2017). In contrast, the ConvLSTM-Attention model offers several advantages,

This architecture is particularly suited to innovation analysis because:

- It accommodates unbalanced panels and irregular time series without listwise deletion (Hochreiter & Schmidhuber, 1997);
- It models non-linearities and interaction effects (e.g., human capital × institutional quality) that linear models miss (Ding et al., 2022);
- Attention weights provide interpretable lag diagnostics, operationalizing theoretical claims about policy gestation periods (Falk, 2012).

Architecture Details: The model processes input sequences $X \in R\ T \times F$, where T=12 (years) and F=5 (GII input pillars). The architecture comprises: Input Layer -MinMax-scaled features. ConvLSTM Layer: 64 hidden units, kernel size = (1, 3), ReLU activation. The 1D convolution operates across features, enabling cross-pillar interaction modeling.

The Multi-Head Attention: 4 heads, each learning distinct temporal weighting schemes. Attention weights $\boldsymbol{\alpha_t}$,are computed as:

$$\alpha_t = softmax\left(\frac{Q_t K_t^T}{\sqrt{d_k}}\right), \qquad \text{Eq. 2}$$

where Q, K are query/key projections of hidden s tates.

Dense Layers: Two fully connected layers (128 → 64 units, ReLU), followed by an output layer (2 units:

Knowledge & Technology Outputs, Creative Outputs). The model was trained using the Adam optimizer with a learning rate of 0.001. It processed data in batches of 32 country-year sequences. To prevent overfitting, a 0.3 dropout rate was applied. The model was trained for up to 200 epochs using Mean Squared Error (MSE) as the loss function, with an early stopping mechanism (patience of 15) to select the best performance.

Interpretability and Validation: To ensure transparency, SHapley Additive exPlanations (SHAP) values (Lundberg & Lee, 2017) were computed to quantify the marginal contribution of each input pillar (institutions, human capital, infrastructure, market sophistication, business sophistication) to predicted outputs. SHAP enables both global feature ranking and local explanations, including stratified analyses by institutional quality (80th percentile threshold: 77.48) and income level (World Bank classification), Model performance was evaluated using R^2, RMSE, and MAE under 5-fold temporal cross-validation to prevent data leakage.
This methodological framework advances prior NIS research by replacing static, linear assumptions with a dynamic, non-linear, and interpretable model—offering a replicable approach for policy simulation in data-constrained, low-income settings like Ethiopia.

3. RESULTS

This section presents the empirical findings derived from both qualitative and quantitative analyses. The results are structured into two parts: (1) descriptive statistics from the stakeholder survey, which contextualize systemic challenges within Ethiopia's National Innovation System (NIS); and (2) predictive modeling outcomes from the ConvLSTM-Attention framework, including model performance, feature importance via SHAP values, and cross-model comparisons.

3.1. Descriptive Findings: Stakeholder Perceptions

A total of 130 stakeholders participated in the survey, representing government agencies (20%), small and large enterprises (30% combined), and research institutions (50%). As shown in Table 2, the sample is dominated by male respondents (60%) and individuals aged 26–35 years (45%), reflecting the demographic profile of active professionals in Ethiopia's science, technology, and innovation (STI) sector. Over 90% hold at least a bachelor's degree, ensuring technical familiarity with NIS concepts.

Survey responses reveal widespread dissatisfaction with current NIS performance. Only 10% of respondents rated Ethiopia's research institutions as "very effective," while 45% considered them "somewhat ineffective" or "very ineffective." Similarly, bureaucratic efficiency in supporting innovation was rated "very inefficient" by 35% of respondents and "somewhat inefficient" by an additional 40%. Intellectual property protection was identified as a "major problem" by 60% of participants, and access to innovation financing was deemed "very inaccessible" or "somewhat inaccessible" by 75%.

When asked to rank barriers by severity, weak coordination between government, research institutes, and industries emerged as the top challenge (ranked first by 42% of respondents), followed by lack of funding (30%) and inadequate policies (18%). Respondents also emphasized the need for policy reform, with 55% identifying business regulations as the area requiring most improvement.

These perceptions align with findings from UNCTAD (2020) and Mezid Nasir Keraga (2023), who document persistent gaps in institutional coherence and implementation capacity within Ethiopia's STI ecosystem.

3.2. Model Performance

As shown in Table 2, the ConvLSTM-Attention model outperformed Panel OLS and random forest benchmarks across all evaluation metrics for both output dimensions. While the Random Forest model improved upon the linear baseline, the ConvLSTM model achieved superior performance. These results indicate strong predictive accuracy and generalizability, confirming that capturing temporal dependencies provides a significant advantage over static non-linear models.

Table 2: Model Performance.

Model	Output Type	R^2	RMSE	MAE
Panel OLS	Knowledge & Technology	0.62	0.28	0.21
	Creative Output	0.58	0.31	0.24
Random Forest	Knowledge & Technology	0.78	0.18	0.16
	Creative Output	0.74	**0.11**	0.12
ConvLSTM-Attention	Knowledge & Technology	**0.89**	**0.11**	**0.09**
	Creative Output	**0.85**	**0.13**	**0.10**

3.3. Feature Importance and SHAP Analysis

To interpret the model's predictions, SHAP (SHapley Additive exPlanations) values were computed (Lundberg & Lee, 2017). Table 3 present global summary plots showing the direction and magnitude of each input's contribution to innovation outputs.

For Knowledge & Technology Outputs (Table 3), Human Capital and Research exhibited the highest mean absolute SHAP value (0.296), followed by Business Sophistication (0.252) and Infrastructure (0.160). High levels of STEM education, researcher density, and R&D expenditure consistently predicted stronger knowledge outputs.

For Creative Outputs (Table 3), Infrastructure was the dominant driver (mean SHAP = 0.477), followed by Business Sophistication (0.366) and Human Capital and Research (0.294). This suggests that digital connectivity, logistics, and energy reliability are foundational for creative industries such as design, media, and software development.

Notably, Institutions—encompassing regulatory quality, political stability, and IP protection—showed positive but relatively lower average contributions (0.098 for KT, 0.126 for Creative). However, conditional analysis revealed a critical moderating role: in countries with low institutional quality, the marginal returns on human capital and infrastructure were significantly diminished. For instance, in low-institution contexts, increased R&D spending showed near-zero or even negative SHAP values for knowledge outputs, indicating wasted investment due to poor governance.

Table 3: Mean SHAP Summary: Global Feature Importance for Knowledge & Technology and Creative Outputs.

Feature	Mean SHAP (KT Output)	Mean SHAP (Creative Output)
Infrastructure	0.16	0.477
Business Sophistication	0.252	0.366
Human Capital and Research	0.296	0.294
Market Sophistication	0.096	0.167
Institutions	0.098	0.126

FIThis table highlights the divergent drivers of innovation globally. Human Capital and Research emerge as the strongest predictors for Knowledge & Technology outputs, whereas Infrastructure and Business Sophistication are the dominant drivers for Creative outputs.

Within the global dataset, Ethiopia ranked among the lowest 20% in both innovation outputs throughout the observation period. Attention weights from the model indicate that reforms prior to 2016 had minimal predictive impact, suggesting delayed system responsiveness. However, rising attention scores post-2018 coincide with the rollout of GTP II initiatives, implying emerging momentum.

4. DISCUSSION

This study set out to diagnose the structural and dynamic constraints within Ethiopia's National Innovation System (NIS) using a mixed-methods approach that integrates stakeholder insights with a machine learning–driven analysis of global innovation dynamics. The findings reveal not only the magnitude of systemic gaps but also the conditional nature of innovation drivers—highlighting that inputs such as human capital and infrastructure yield meaningful returns only when embedded within capable institutional and market environments. This section interprets these results, situates them within broader theoretical and regional contexts, and outlines their implications for policy and future research.

A central insight from the SHAP analysis is what we term the "institutional paradox": in low-institutional-quality settings like Ethiopia (GII Institutions score: 32.7 in 2022), investments in human capital and research produce negligible or even slightly negative marginal effects on knowledge and technology outputs. This finding challenges the conventional wisdom that increasing STEM enrollment or R&D expenditure alone will catalyze innovation. Instead, it aligns with recent scholarship emphasizing that institutional quality—encompassing regulatory coherence, rule of law, and IP enforcement—acts as a systemic enabler that modulates the productivity of other inputs (Egbetokun et al., 2017; Danta & Rath, 2024).

Ethiopia's experience exemplifies this dynamic. Despite policy commitments under GTP II and the establishment of science and technology universities, weak coordination across ministries, frequent regulatory shifts, and ineffective IP protection (cited by 60% of survey respondents) create an environment of uncertainty that deters long-term innovation investment. As a result, even highly educated graduates struggle to find pathways to apply their skills, and firms remain reluctant to engage in R&D. This explains the persistent "inputs without outcomes" pattern observed in Ethiopia's NIS—a phenomenon also documented in UNCTAD's (2020) policy review.

The analysis further reveals that infrastructure's impact on innovation is not universally positive. In low- and lower-middle-income countries, infrastructure exhibits a negative association with knowledge and technology outputs (mean SHAP = –0.183), whereas it is strongly positive in upper-income contexts (mean SHAP = 0.339). This threshold effect suggests that physical infrastructure—such as electricity, roads, and internet—only becomes an innovation enabler when complemented by absorptive capacity, skilled labor, and functional markets.

Knowlage and technolgy output   Creative output

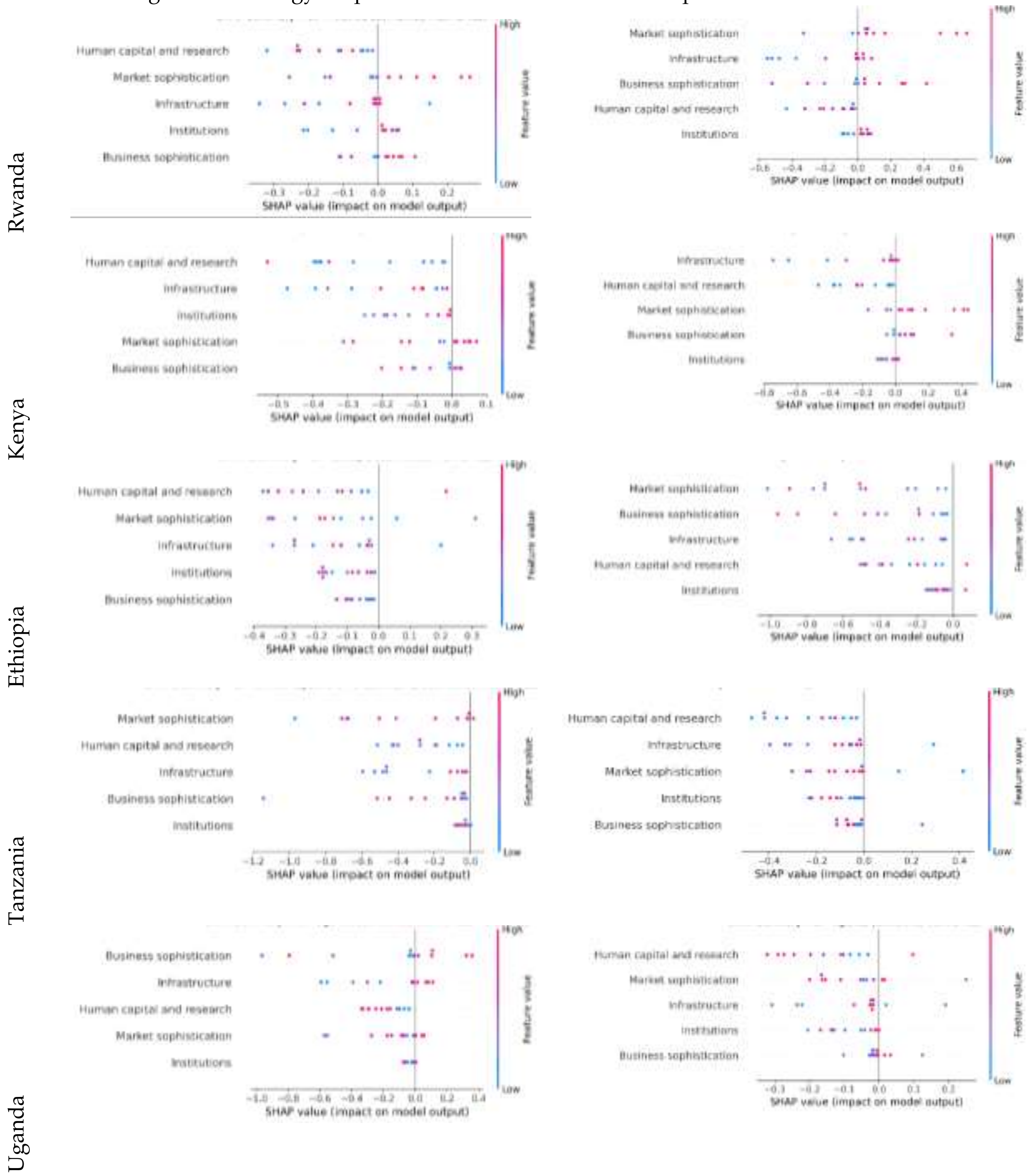

Figure 2: SHAP plot for week institute African countries

Figure 2 SHAP plot for week institute African countries. (These plots illustrate the "institutional paradox." In countries with low institutional scores, high feature values (indicated by red dots) for inputs like Infrastructure and Human Capital frequently cluster near zero or on the negative side of the SHAP axis. This indicates that without strong governance, these investments yield negligible or even negative marginal returns for innovation outputs)

In Ethiopia, where 45% of R&D funds are allocated to machinery and buildings rather than actual research (Belachew Alemayehu, 2021), infrastructure investments may crowd out genuine innovation activity. Without parallel improvements in governance and human capital, new laboratories or broadband networks risk remaining underutilized. This finding resonates with Lall and Pietrobelli's (2005) argument that technology adoption in developing countries requires "systemic" rather than "component" investments.

The evidence supports a phased, sequenced reform agenda—not a list of parallel recommendations. The sequence is dictated by the causal logic of the institutional paradox: institutional reform must precede or accompany resource-intensive investments associated with higher predictive values. Below is a three-phase roadmap grounded in the study's empirical findings.

4.1. Creative Vs. Knowledge-Based Innovation Pathways

The SHAP results also uncover divergent innovation pathways. While human capital dominates knowledge and technology outputs, business sophistication is the strongest predictor of creative outputs (mean SHAP = 0.477). This distinction is critical for policy design. Ethiopia may lack the institutional and scientific base to compete in high-tech patenting in the short term, but it possesses significant potential in creative industries—such as agri-processing, design, digital content, and cultural goods—provided that market access, branding, and financing mechanisms are strengthened.

Notably, 52% of respondents identified "Leveraging Agri-Tech for Food Security" as the top strategic priority for the next decade, reflecting the country's agrarian base and pressing developmental needs. This suggests a pragmatic, demand-driven innovation agenda that aligns with local realities rather than global benchmarks.

4.2. Comparative Insights: Ethiopia In the East African Context

When compared to regional peers, Ethiopia lags significantly in key NIS functions. Rwanda (GII rank 91 in 2023) has prioritized institutional reform—establishing specialized IP courts, streamlining business registration, and fostering university–industry linkages—resulting in a 25% increase in collaborative R&D projects between 2015 and 2022 (Yongabo & Göransson, 2022). Kenya (rank 83) has leveraged its vibrant fintech ecosystem and diaspora networks to attract venture capital and scale digital innovations.

In contrast, Ethiopia's NIS remains fragmented. Only 26% of respondents rated research institutions as "somewhat" or "very" effective, and 74% cited weak collaboration among government, academia, and industry as a major barrier. This "Triple Helix" disconnects limits knowledge spillovers and commercialization—key mechanisms through which innovation translates into economic growth.

4.3. Contributions And Generalizability

This study makes three interlinked contributions. Conceptually, it refines NIS theory for low-income contexts by demonstrating that innovation drivers are not additive but conditional—mediated by institutional and economic thresholds. Methodologically, it pioneers the use of ConvLSTM-Attention with SHAP interpretability to model non-linear, lagged dynamics in panel data, offering a replicable framework for policy simulation in data-scarce environments. Practically, it provides a sequenced, evidence-based roadmap for Ethiopia that prioritizes institutional reform as a prerequisite for effective resource deployment.

However, the findings are not universally generalizable. They apply most directly to low-income, institutionally weak economies with centralized innovation governance and limited private-sector R&D. The model's reliance on GII indicators—while enabling cross-national comparison—may underrepresent informal or grassroots innovation.

4.4. Policy Implication

The evidence supports a phased approach to NIS strengthening:

- Foundational Institutional Reforms: Adopt a National Innovation Strategy with cross-ministerial coordination; modernize IP enforcement through digital registries and specialized courts; expand regulatory sandboxes in agritech and fintech.
- Human Capital Transformation: Shift STEM education toward critical thinking and digital literacy; establish dual-track training with entrepreneurial competencies; launch a Talent Retention Initiative to counter brain drain.

- Innovation Finance Architecture: Create a National Innovation Fund with public–private co-investment; introduce R&D tax credits and first-loss guarantees; develop SME innovation credit lines.
- Structured Collaboration Mechanisms: Tie university funding to industry engagement metrics; establish fully resourced Technology Transfer Offices; catalyze sectoral innovation clusters in priority areas.

These measures are aligned with both Ethiopia's GTP II and the African Union's STISA-2024, which calls for 1% of GDP to be allocated to R&D—a target Ethiopia currently misses (0.3–0.51%). Critically, the focus must shift from input volume to output quality: ensuring that R&D funds support actual research, not just infrastructure. Finally, innovation policy must be inclusive. Survey respondents described Ethiopia's ecosystem as "exclusionary" along gender and regional lines. Future reforms should embed equity metrics into funding, governance, and leadership to ensure that innovation benefits all segments of society.

5. CONCLUSION

This study has investigated the structural and dynamic constraints within Ethiopia's National Innovation System (NIS) through an integrated mixed-methods approach combining stakeholder insights with a machine learning–driven analysis of global innovation trajectories. By applying a ConvLSTM-Attention model augmented with SHAP interpretability to 12 years of panel data from 105 countries, the research identifies not only the relative importance of different innovation drivers but also their context-contingent effects—particularly the moderating role of institutional quality.

Three core implications emerge from this analysis. First, the identification of the 'institutional paradox' confirms that in governance-constrained environments like Ethiopia, foundational institutional reforms—such as regulatory coherence and IP enforcement—must precede or tightly accompany investments in education and infrastructure. Without this sequencing, conventional innovation inputs risk yielding diminishing returns.

Second, recognizing that innovation pathways diverge across output types allows for more pragmatic policy design. Rather than prematurely chasing high-tech patenting, Ethiopia can achieve greater near-term socio-economic impact by leveraging its business sophistication to drive creative outputs in sectors aligned with its agrarian and digital development needs.

Finally, addressing the systemic lag behind regional peers requires moving beyond fragmented policy implementation. The pervasive coordination gaps among government, academia, and industry demand the establishment of formalized, fully resourced 'Triple Helix' collaboration mechanisms to translate innovation potential into measurable economic growth.

6. CONTRIBUTIONS AND LIMITATIONS

Theoretically, this study advances NIS theory for low-income economies by demonstrating that innovation inputs do not act additively but interact dynamically and non-linearly, with institutional quality serving as a critical enabler. Methodologically, it pioneers the use of ConvLSTM-Attention networks with SHAP-based interpretation in social science research, offering a replicable framework for modeling complex, lagged relationships in longitudinal panel data—especially valuable in contexts with limited causal identification options.

Practically, the findings support a sequenced reform agenda: institutional strengthening must precede or accompany investments in human capital and infrastructure. Policy recommendations include establishing a National Innovation Strategy with cross-ministerial coordination, modernizing IP enforcement, launching a national innovation fund, and mandating Technology Transfer Offices in public universities.

Nonetheless, several limitations must be acknowledged. First, the reliance on Global Innovation Index (GII) data, while enabling cross-national comparability, may underrepresent informal innovation and grassroots technological adaptation—forms prevalent in agrarian economies like Ethiopia's. Second, while the model captures predictive relationships and temporal dynamics, it does not establish causality; future work could employ natural experiments or instrumental variable designs to strengthen causal inference. Third, the qualitative sample, though purposively selected, is not statistically representative, limiting generalizability of survey responses.

7. FUTURE RESEARCH DIRECTIONS

Future studies should extend this framework by incorporating firm-level panel data to examine micro-foundations of innovation, particularly in the private sector. Comparative analyses across African subregions—using similar ML interpretability tools—could test the transferability of the institutional paradox hypothesis. Additionally, integrating satellite accounts for informal sector innovation would provide a more holistic view of national knowledge systems.

Moreover, the ConvLSTM-SHAP methodology developed here can be applied beyond innovation policy—to areas such as health system resilience, educational reform, or climate adaptation—where complex, lagged, and non-linear dynamics challenge traditional econometric approaches.

In conclusion, Ethiopia's journey toward an innovation-led development model requires more than increased funding or isolated reforms. It demands a systemic rethinking of how institutions, policies, and actors interact over time. By combining rigorous data science with grounded stakeholder insight, this study offers both a diagnostic tool and a strategic roadmap—one that not only applies to Ethiopia but holds lessons for other latecomer economies striving to transform knowledge into inclusive growth.

REFERENCES

Acemoglu, D., & Robinson, J. A. (2012). Why nations fail: The origins of power, prosperity, and poverty. Crown Business.

Aghion, P., Howitt, P., & Mayer-Foulkes, D. (2009). The effect of financial development on convergence: Theory and evidence. Quarterly Journal of Economics, 124(1), 215–256. https://doi.org/10.1162/qjec.2009.124.1.215

Alemayehu, B. (2021). R&D expenditure and innovation performance in Ethiopian manufacturing irms [Unpublished manuscript]. Addis Ababa University.

Araya, M. (2023). The impact of R&D on firm productivity in Ethiopia: Evidence from enterprise survey data. Journal of African Business, 24(3), 412–428. https://doi.org/10.1080/15228916.2022.2045678

Baltagi, B. H. (2008). Econometric analysis of panel data (4th ed.). John Wiley & Sons.

Barasa, L. (2019). Technical efficiency of manufacturing firms in Sub-Saharan Africa: The role of innovation inputs. Technovation, 87, 101952. https://doi.org/10.1016/j.technovation.2019.101952

Baris, S. (2019). The impact of institutional quality on innovation: Evidence from OECD countries. Economic Research-Ekonomska Istraživanja, 32(1), 2553–2571. https://doi.org/10.1080/1331677X.2019.1645720

Batista, G. E. A. P. A., & Monard, M. C. (2002). A study of K-Nearest Neighbour as an imputation method. Proceedings of the Second International Conference on Hybrid Intelligent Systems, 87, 281–291.

Besha, T. (2020). University-industry linkage and innovation in Ethiopia: Challenges and prospects. African Journal of Science, Technology, Innovation and Development, 12(5), 601–612. https://doi.org/10.1080/20421338.2019.1695102

Bogliacino, F., Codagnone, C., & Montealegre, F. (2020). The Global Innovation Index: A critical review. Science and Public Policy, 47(5), 723–733. https://doi.org/10.1093/scipol/scaa035

Chang, H. (2020). South Korea's innovation system: From imitation to leadership. Asian Journal of Technology Innovation, 28(1), 1–22. https://doi.org/10.1080/19761597.2020.1725289

Chen, Y., & Puttitanun, T. (2005). Intellectual property rights and innovation in developing countries. Journal of Development Economics, 78(2), 474–493. https://doi.org/10.1016/j.jdeveco.2004.11.005

Choudhry, N., & Ponzio, J. (2020). Intellectual property rights and innovation: Evidence from developing countries. World Development, 135, 105075. https://doi.org/10.1016/j.worlddev.2020.105075

Cirera, X. (2023). Technology adoption and productivity in Ethiopian firms (World Bank Policy Research Working Paper No. 10345). World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099125303072546903/p1808340d1177f03c0ab180057556655523

Creswell, J. W., & Plano Clark, V. L. (2017). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

Danta, A., & Rath, N. M. (2024). Institutional quality and human capital synergy in driving innovation: Evidence from Asian economies. Technological Forecasting and Social Change, 199, 123145. https://doi.org/10.1016/j.techfore.2023.123145

Dennis, A., Osei, R. D., & Quartey, P. (2024). Digital infrastructure, human capital, and innovation in Africa. Journal of African Economies, 33(1), 1–25. https://doi.org/10.1093/jae/ejad022

Ding, H., Li, Y., & Wang, Y. (2022). Configurations of national innovation performance: A fuzzy-set qualitative comparative analysis. Technological Forecasting and Social Change, 184, 122001. https://doi.org/10.1016/j.techfore.2022.122001

Edler, J., & Fagerberg, J. (2017). Innovation policy: What, why, and how. Oxford Review of Economic Policy, 33(1), 2–23. https://doi.org/10.1093/oxrep/grx004

Egbetokun, A., Oyelaran-Oyeyinka, B., & Adetunji, O. (2017). Institutional quality and innovation in sub-Saharan Africa. Science and Public Policy, 44(5), 671–682. https://doi.org/10.1093/scipol/scw075

Ethiopian Capital Market Authority. (2023). Fintech regulatory sandbox: Interim evaluation report. Addis Ababa: ECMA.

Federal Democratic Republic of Ethiopia. (2010). Science and technology policy. Ministry of Science and Technology.

Freeman, C. (1987). Technology policy and economic performance: Lessons from Japan. Pinter Publishers.

Gebrehiwot, T. (2016). Human capital and economic growth in Ethiopia: An ARDL approach. Journal of Economics and Sustainable Development, 7(15), 12–21.

Gouldson, A. (2020). Ethiopia's national innovation system: A review of strengths and weaknesses. UNCTAD STI Policy Review.

Harmes-Liedtke, U. (2010). Innovation systems in developing countries: A handbook. GIZ.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Hou, W. (2017). Infrastructure and innovation in Africa: Evidence from Ethiopia. African Development Review, 29(S1), S45–S57. https://doi.org/10.1111/1467-8268.12245

Jerez, J. M., Molina, I., García-Laencina, P. J., Alba, E., Ribelles, N., Martín-Martín, M., & Franco, L. (2010). Missing data imputation using statistical and machine learning methods in a real breast cancer prognosis dataset. Artificial Intelligence in Medicine, 50(2), 105–115. https://doi.org/10.1016/j.artmed.2010.05.002

Kayal, A. A. (2008). National innovation systems in developing countries: A conceptual framework. International Journal of Innovation and Learning, 5(6), 645–662. https://doi.org/10.1504/IJIL.2008.018955

Kebebe, E. (2019). Innovation systems and livestock development in Ethiopia. ILRI Research Report. International Livestock Research Institute.

Keraga, M. N. (2023). R&D, innovation, and firm productivity in Ethiopia. African Journal of Economic and Management Studies, 14(2), 210–225. https://doi.org/10.1108/AJEMS-05-2022-0156

Kolomytseva, O. (2020). Government policy and research institutes: The case of Ukraine. Science and Public Policy, 47(4), 512–521. https://doi.org/10.1093/scipol/scaa025

Kurpayanidi, K. (2023). National innovation system in Uzbekistan: Status and challenges. Journal of the Knowledge Economy, 14(2), 1890–1912. https://doi.org/10.1007/s13132-022-01058-2

Lall, S., & Pietrobelli, C. (2005). Innovation capabilities and exports in developing countries. World Development, 33(10), 1673–1688. https://doi.org/10.1016/j.worlddev.2005.05.002

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765–4774.

Lundvall, B. Å. (1992). National systems of innovation: Towards a theory of innovation and interactive learning. Pinter Publishers.

Lundvall, B. Å. (2007). National innovation systems—Analytical concept and development tool. Industry and Innovation, 14(1), 95–119. https://doi.org/10.1080/13662710601130863

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(s1), 631–652. https://doi.org/10.1111/1468-0084.61.s1.13

Morgan, D. L. (2014). Pragmatism as a paradigm for social research. Qualitative Inquiry, 20(8), 1045–1053. https://doi.org/10.1177/1077800413513733

National Planning Commission. (2016). Growth and Transformation Plan II (GTP II): 2015/16–2019/20. Federal Democratic Republic of Ethiopia.

Nelson, R. R. (1993). National innovation systems: A comparative analysis. Oxford University Press.

Nelson, R. R., & Rosenberg, N. (1993). Technical innovation and national systems. In R. R. Nelson (Ed.), National innovation systems: A comparative analysis (pp. 3–21). Oxford University Press.

Organisation for Economic Co-operation and Development. (2021). The innovation imperative: Contributing to productivity, growth and well-being. OECD Publishing. https://doi.org/10.1787/9789264276284-en

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5, Part 2), S71–S102. https://doi.org/10.1086/261725

Shkabatur, J. (2021). Innovation policy in low-income countries: The case of Ethiopia. World Development Perspectives, 23, 100332. https://doi.org/10.1016/j.wdp.2021.100332

Suhatman, R. (2024). Human capital and economic growth in Ethiopia: A unidirectional relationship. Journal of Economics and Development Studies, 12(1), 45–59.

United Nations Conference on Trade and Development. (2020). Science, technology and innovation policy review: Ethiopia. United Nations. https://unctad.org/publication/science-technology-and-innovation-policy-review-ethiopia-2020

Weerasinghe, R. N., Jayawardane, A. K. W., & Huang, Q. (2023). National innovation systems in developing countries: A critical review and conceptual framework. Technovation, 121, 102601. https://doi.org/10.1016/j.technovation.2022.102601

World Intellectual Property Organization. (2023). Global Innovation Index 2023: Innovation in the face of uncertainty. WIPO. https://www.globalinnovationindex.org

Yongabo, S., & Göransson, B. (2022). Constructing a national innovation system in Rwanda. African Journal of Science, Technology, Innovation and Development, 14(4), 521–533. https://doi.org/10.1080/20421338.2021.1935067