Determinants of Agricultural Trade Competitiveness in Zambia: A Time-Series Cointegration Analysis of Technology, Energy, Investment, Growth, Global Value Chains, and Institutional Quality (1990–2024)

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ABSTRACT

Zambia's agricultural sector employs over 60% of the rural workforce yet captures minimal value in international markets, exporting predominantly unprocessed primary commodities. Identifying which structural factors most strongly drive agricultural trade competitiveness, and how they interact over time, is essential for designing effective policy in a resource-rich but structurally underdeveloped economy. This study investigates the long and short-run determinants of agricultural trade competitiveness in Zambia over 1990-2024, examining the joint role of technological innovation, renewable and non-renewable energy consumption, foreign direct investment, economic growth, global value chain integration, and institutional quality. Annual time-series data are analyzed within an integrated econometric framework comprising Augmented Dickey–Fuller unit root tests, Autoregressive Distributed Lag (ARDL) bounds testing, a Vector Error Correction Model (VECM), Granger causality analysis, mediation analysis, and Fully Modified OLS for robustness. The results reveal that all seven determinants exert statistically significant long-run effects. Global value chain integration (β= 0.517, p < 0.01) and technological innovation (β = 0.462, p < 0.01) emerge as the dominant drivers, followed by economic growth (0.398), institutional quality (0.336), renewable energy (0.285), foreign direct investment (0.241), and a marginally negative effect of non-renewable energy (−0.172). The error correction term (−0.641, p < 0.001) implies that approximately 64% of deviations from long-run equilibrium are corrected within one year. Mediation analysis confirms that technological innovation operates partially through GVC participation (indirect effect = 0.238) and institutional capacity (0.147), while FDI partly enhances competitiveness through technological transfer. The findings indicate that agricultural competitiveness is system-driven rather than dependent on a single lever, supporting an integrated, sequenced policy strategy combining short-term institutional reform and medium-term infrastructure expansion and value-chain deepening. The study extends endogenous growth, national innovation systems, and global value chain theory to a low-institutional-capacity Sub-Saharan African setting and provides empirically grounded guidance for sustainable agricultural transformation.

Keywords: agricultural trade competitiveness; technological innovation; global value chains; renewable energy; institutional quality; ARDL bounds testing; Zambia; sustainable agriculture

INTRODUCTION

Zambia's agricultural sector embodies a structural paradox at the heart of Sub-Saharan African development: it employs over 60% of the rural workforce yet contributes only 7–9% of GDP and captures minimal value in international markets [1, 2]. Agricultural exports remain dominated by primary, unprocessed commodities maize, soybeans, tobacco, sugar traded with little value addition into volatile world markets. Neighboring countries with comparable agro-ecological endowments, including Malawi and Tanzania, have achieved significantly higher agricultural export values per capita, raising fundamental questions about why Zambia's natural resource advantage has not translated into competitive market positioning [3, 4].

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Empirical evidence indicates that innovative technologies improved seeds, mechanization, conservation agriculture, digital advisory services demonstrably enhance agricultural productivity and trade performance [5]. Agricultural digitalization can improve access to information, advisory services, and market connectivity, strengthening smallholder responsiveness to production risks and market signals. Yet adoption of such technologies remains uneven across Africa, largely because of gaps in infrastructure, extension services, and access to finance that constrain technology utilization by farmers and agribusinesses [3, 6]. Zambia exemplifies this adoption paradox: conservation agriculture practices tested at the Zambia Agriculture Research Institute (ZARI) remain adopted by fewer than 15% of farmers two decades after their introduction, despite high profitability in trials. The constraint is not technological but institutional weak extension delivery, limited credit access, and insecure land tenure prevent sustained productive investment [7, 8].

Beyond technology, agricultural competitiveness depends on a constellation of structural conditions whose interactions remain insufficiently understood for Zambia's specific context. Energy access determines whether mechanization, irrigation, cold-chain logistics, and agro-processing can operate at competitive cost [11, 13]. Foreign direct investment introduces capital, technology, and market networks, yet its competitiveness effects depend on absorptive capacity [18, 21]. Economic growth shapes the macroeconomic envelope within which agricultural transformation occurs [28, 29]. Global value chain (GVC) integration provides a dynamic upgrading channel that converts technological capability into international value capture [30, 31]. Institutional quality conditions the effectiveness of every other determinant by shaping incentives, transaction costs, and public goods provision [38, 39, 40].

Despite a growing literature on agricultural productivity and technology use in developing countries, three substantive gaps motivate the present study. First, most existing work on Zambia focuses on micro-level adoption or productivity outcomes, with limited analysis of how innovation translates into trade performance at the national level [7, 58]. Second, the literature has not adequately examined how multiple structural determinants jointly shape competitiveness through both direct and mediated pathways, treating innovation, energy, FDI, growth, GVC integration, and institutions as separate research streams rather than as a coordinated system. Third, no prior empirical analysis employs time-series cointegration methods to examine the joint long-run and short-run dynamics of agricultural trade competitiveness in Zambia, despite the substantive distinction between immediate productive effects and slowly accumulating structural relationships.

Against this backdrop, the present study makes three contributions. First, it develops and empirically validates an integrated multi-determinant framework that situates technological innovation within a structurally interdependent system of energy, capital, growth, integration, and institutional conditions, drawing on endogenous growth theory [44, 45], national innovation systems theory [46, 47], and global value chain theory [30, 37]. Second, it provides the first time-series cointegration evidence on Zambia's agricultural competitiveness, using

ARDL bounds testing, a Vector Error Correction Model (VECM), Granger causality analysis, and Fully Modified OLS estimation over 1990–2024 to quantify both equilibrium elasticities and short-run adjustment dynamics. Third, it tests three mediation pathways TI→GVC→TC, TI→INST→TC, and FDI→TI→TC establishing the structural interdependencies that conventional single-determinant or loosely specified multi-variable models cannot detect.

The central research questions are: *What are the long-run and short-run elasticities of Zambia's agricultural trade competitiveness with respect to technological innovation, energy structure, foreign capital, economic growth, global value chain integration, and institutional quality?* The study further asks whether the technology competitiveness pathway is mediated by GVC integration and institutional capacity, and whether the structural determinants Granger-cause competitiveness or merely co-vary with it. Embedding these questions within the wider sustainability agenda, the paper highlights how a sequenced, evidence-based strategy can transform Zambia's agricultural sector along trajectories aligned with sustainable development goals on food security, decent work, climate action, and partnership for goals.

The remainder of the paper is organized as follows. Section 2 reviews the literature, develops the theoretical framework, and articulates the four hypotheses (with sub-hypotheses) tested in the empirical analysis. Section

3 presents the methodology, model specification, variable measurement, and data sources. Section 4 reports descriptive statistics, correlation analysis, ARDL bounds and long-run estimates, short-run dynamics, Granger causality, mediation analysis, and FMOLS robustness checks. Section 5 discusses the findings in light of theory and prior evidence and reflects on their structural implications for Zambia. Section 6 concludes with sequenced policy implications, limitations, and avenues for future research.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Technological Innovation and Agricultural Competitiveness

A persistent puzzle in agricultural development is the *adoption paradox*: technologies with proven field efficacy frequently fail to generate sustained productivity gains at scale in low-income economies. Direct empirical evidence linking technology-driven productivity growth to agricultural export competitiveness at the national level is established by Nin-Pratt and Yu [10], whose cross-country analysis of 47 developing economies demonstrates that total factor productivity growth driven by technological adoption is the principal source of improvements in revealed comparative advantage in agriculture, particularly for non-traditional products requiring quality compliance and processing standards.

Ruzzante et al. [9] synthesis evidence from a meta-analysis spanning 38 developing countries, finding that technology adoption raises agricultural productivity by an average of 12% with variance so large that the 95th-percentile effect exceeds three times the median. This heterogeneity, attributable to differences in extension service quality, credit access, input market functionality, and agro-ecological conditions, implies that aggregate competitiveness effects cannot be inferred from productivity findings without accounting for structural enablers. Choruma, Dirwai, and Mutenje [5] provide the most comprehensive recent synthesis of agricultural digitalization in Sub-Saharan Africa, documenting across 87 studies how precision-farming technologies, satellite crop monitoring, and mobile advisory platforms improve smallholder productivity and market responsiveness, while emphasizing that weak rural connectivity, user capability gaps, and prohibitive cost structures systematically limit diffusion.

Porteous [6] identifies a complementary mechanism through which innovation enhances competitiveness: *trade cost reduction*. His analysis demonstrates that technological improvements in logistics, market information systems, and supply chain coordination innovation embodied in trade facilitation infrastructure generate competitiveness gains distinct from on-farm productivity effects. A 10% reduction in effective trade costs is associated with a 6–8% increase in agricultural export value in African markets, with disproportionate gains among small and medium agribusinesses for whom transaction costs were previously prohibitive.

Chisanga and Odhiambo's [7] Zambia-specific analysis documents that persistent underinvestment in public agricultural R&D and institutional gaps in extension delivery have constrained smallholder technology uptake despite successive national agricultural policy commitments. Public agricultural R&D expenditure in Zambia has rarely exceeded 0.4% of agricultural GDP, less than half the CAADP benchmark of 1%, resulting in a weak pipeline of locally adapted technologies and limited extension capacity to disseminate existing innovations. Collectively, the technological innovation literature establishes a robust positive relationship with agricultural competitiveness while simultaneously identifying the conditionalities that attenuate this relationship in low-institutional-capacity settings.

Energy Structure and Trade Competitiveness

Energy access and its sustainability dimension influence agricultural trade competitiveness through three interrelated channels: production costs, processing and cold-chain reliability, and environmental sustainability requirements increasingly embedded in export market standards. The foundational evidence on renewable energy's role in economic performance is provided by Apergis and Payne [11], whose panel analysis of 16 emerging economies establishes a positive bidirectional causal relationship between renewable energy consumption and real output growth. Usman et al. [13] provide the most direct link between renewable energy consumption and export competitiveness, demonstrating that renewable energy use significantly contributes to economic complexity and export diversification through industrial upgrading: lower and more stable energy costs make energy-intensive value-added processing operations economically viable.

Porter and van der Linde's [14] innovation-offsets framework introduces a competitiveness consideration absent from purely cost-oriented analyses: environmental regulation and clean energy standards can generate innovation rents and first-mover advantages by compelling producers to develop cleaner, more efficient production methods ahead of competitors. For Zambia, which benefits from abundant hydroelectric and solar potential, the early development of a clean energy-powered agricultural export sector could generate a sustainability differentiation advantage in EU and Asian markets where carbon footprint, deforestation-free production, and environmental compliance are increasingly binding import conditions.

Non-renewable energy's role is more ambiguous, operating through fundamentally different channels: it supports productive capacity in the short run through mechanized operations and logistics, while introducing cost volatility, environmental penalties, and competitiveness risks over longer time horizons [15, 17]. For Zambia, which imports virtually all of its petroleum products and therefore lacks domestic price stabilization capacity, this transmission is direct and unmitigated, motivating the expectation of a marginally negative long-run NRE coefficient.

FDI, Economic Growth, and Agricultural Trade Performance

Foreign direct investment's contribution to agricultural trade competitiveness has generated an extensive and empirically contested literature. Borensztein, De Gregorio, and Lee [18] establish the foundational empirical result: FDI contributes to productivity growth and technological upgrading only when the host country possesses sufficient absorptive capacity, operationalized as a minimum human capital stock. Below this threshold, FDI's technology transfer function is attenuated. Blomström and Kokko [19] provide the theoretical mechanism through which FDI generates positive spillovers via horizontal demonstration effects and vertical supplier development requirements that mandate technical improvements along the supply chain.

Gui-Diby and Renard [20] provide SSA-specific evidence demonstrating that FDI inflows significantly promote industrialization and productive capacity, including in agro-processing sectors, while documenting sectoral heterogeneity: FDI in resource extraction generates fewer employment and productivity spillovers than FDI in manufacturing and agro-processing. Ibrahim, Musah, and Sare [21] document that agricultural FDI inflows in Zambia have been disproportionately concentrated in large-scale commercial farming operations, with limited supply chain linkages to the smallholder producers who constitute over 80% of agricultural production.

The relationship between macroeconomic growth and agricultural trade competitiveness is theoretically bidirectional. Balassa's [26] export-led growth framework provides the foundation: countries that expand their export sectors develop comparative advantages through scale economies, learning-by-exporting effects, and resource reallocation toward higher-productivity tradable activities. Awokuse [28] provides time-series cointegration evidence across multiple Sub-Saharan African economies demonstrating that GDP growth is cointegrated with export competitiveness and that domestic economic expansion strengthens the supply-side foundations of export capacity through infrastructure investment, institutional development, and technological adoption.

Global Value Chain Integration and Institutional Quality as Enabling Conditions

Global value chain theory has fundamentally reoriented the analysis of agricultural trade competitiveness from a static comparative advantage framework to a dynamic upgrading process within governed international production networks. Gereffi, Humphrey, and Sturgeon's [30] foundational governance typology distinguishes five chain structures (market, modular, relational, captive, hierarchical) characterized by the complexity of transactions, the codifiability of product specifications, and the capability of the supplier base. Most agricultural GVCs in developing countries exhibit captive or relational governance: lead firms specify quality standards, production protocols, traceability systems, and delivery schedules that suppliers must meet as a precondition of market access.

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Kummritz, Taglioni, and Winkler [31] provide rigorous econometric evidence on GVC participation's productivity effects, demonstrating using decomposed value-added trade data for over 50 countries that both backward and forward participation significantly raise labour productivity and GDP per capita. Koopman, Wang, and Wei's [32] value-added decomposition framework directly applied in this study resolves the measurement problem of conflated domestic and foreign value-added components in gross export statistics. Zhang and Sun [33] extend the GVC–competitiveness analysis to agricultural total factor productivity, demonstrating that agricultural GVC participation significantly raises TFP through technology spillovers and institutional learning effects.

Institutional quality is increasingly recognized as a first-order determinant of agricultural trade competitiveness. North's [38] foundational framework defines institutions as the formal rules, informal constraints, and enforcement mechanisms structuring human interaction, arguing that these structures determine the incentive environment for investment, innovation, and exchange. Acemoglu, Johnson, and Robinson's [39] landmark empirical work demonstrates that institutional quality is the dominant determinant of cross-country income differences. Kaufmann, Kraay, and Mastruzzi's [40] Worldwide Governance Indicators provide the empirical framework used in this study, capturing governance across six dimensions, of which Government Effectiveness, Regulatory Quality, and Rule of Law are most directly relevant to agricultural competitiveness.

Theoretical Foundations

The analysis integrates three theoretical perspectives. *Endogenous growth theory* [44, 45] posits that knowledge accumulation and technological progress are the principal drivers of long-term growth and provides the rationale for why innovation directly enhances competitiveness through productivity gains and knowledge spillovers. *National innovation system (NIS) theory* [46, 47] shifts the analytical unit from the individual firm to the networked institutional environment within which innovation is generated, diffused, and applied: knowledge creation is a social process mediated by institutional relationships among firms, research organizations, universities, government agencies, and international partners. *Global value chain theory* [30, 37] provides a relational framework for understanding how developing-country producers navigate and upgrade within international production networks, replacing static comparative advantage with a dynamic upgrading process within governance structures that determine value capture.

The three frameworks are not additive but structurally integrated: endogenous growth theory explains the mechanisms through which technological knowledge generates sustained productivity gains; NIS theory explains the institutional conditions that determine whether these mechanisms operate effectively; and GVC theory explains how international production network relationships amplify, transmit, and condition the competitiveness returns from domestic technological and institutional investment. This integration generates specific empirical predictions: institutional quality should both directly affect competitiveness and moderate the technology competitiveness relationship; GVC integration should be both a direct determinant of competitiveness and a channel through which technology improvements translate into export performance; and the simultaneous estimation of all seven theoretically grounded determinants reflects the genuine systemic nature of agricultural trade competitiveness.

Hypotheses Development

Building on this synthesis, the study tests four main hypotheses with sub-hypotheses where energy structure and external capital admit theoretically distinct components.

Technological innovation occupies the core of the framework, serving as the primary productivity-driven mechanism through which endogenous growth and NIS dynamics translate into competitive advantage in international agricultural markets [10, 9, 5]. We therefore propose:

Hypothesis 1 (H1). Technological innovation exerts a positive and statistically significant long-run effect on agricultural trade competitiveness in Zambia.

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Energy availability and its sustainability profile constitute critical enabling conditions, with renewable and non-renewable sources operating through fundamentally different channels. The Porter–van der Linde innovation-offsets framework [14] and the renewable energy–growth literature [11, 13] both identify clean, reliable energy access as a source of productive efficiency and competitive differentiation. Non-renewable energy's role is more ambiguous, providing productive capacity in the short run while introducing cost volatility and environmental constraints over the long run [15, 17].

Hypothesis 2a (H2a). Renewable energy consumption exerts a positive and statistically significant long-run effect on agricultural trade competitiveness in Zambia.

Hypothesis 2b (H2b). Non-renewable energy consumption exerts a statistically significant long-run effect on agricultural trade competitiveness in Zambia, with a negative direction expected over the long run reflecting cost and environmental constraints associated with fossil fuel dependence.

Foreign direct investment provides external capital, technology transfer, and market network access whose competitiveness returns depend on absorptive capacity [18, 19, 20]. Economic growth, proxied by real GDP growth, captures the macroeconomic envelope through which fiscal capacity, infrastructure investment, and structural transformation reach the agricultural sector [26, 28, 29].

Hypothesis 3a (H3a). Foreign direct investment positively influences agricultural trade competitiveness in Zambia.

Hypothesis 3b (H3b). Economic growth positively influences agricultural trade competitiveness in Zambia.

Global value chain integration and institutional quality function as enabling conditions that amplify the competitiveness returns to other determinants [30, 31, 33, 38, 39]. Their dual role as direct determinants and as mediating channels, generates the prediction that they should both directly influence competitiveness and partially mediate the technology competitiveness pathway, a prediction tested through mediation analysis.

Hypothesis 4a (H4a). Global value chain integration exerts a positive and statistically significant long-run effect on agricultural trade competitiveness in Zambia.

Hypothesis 4b (H4b). Institutional quality exerts a positive and statistically significant long-run effect on agricultural trade competitiveness in Zambia.

Figure 1 summarizes the integrated framework: seven theoretically grounded determinants jointly shape agricultural trade competitiveness, with technological innovation operating partly through GVC and institutional channels (mediation pathways tested separately).

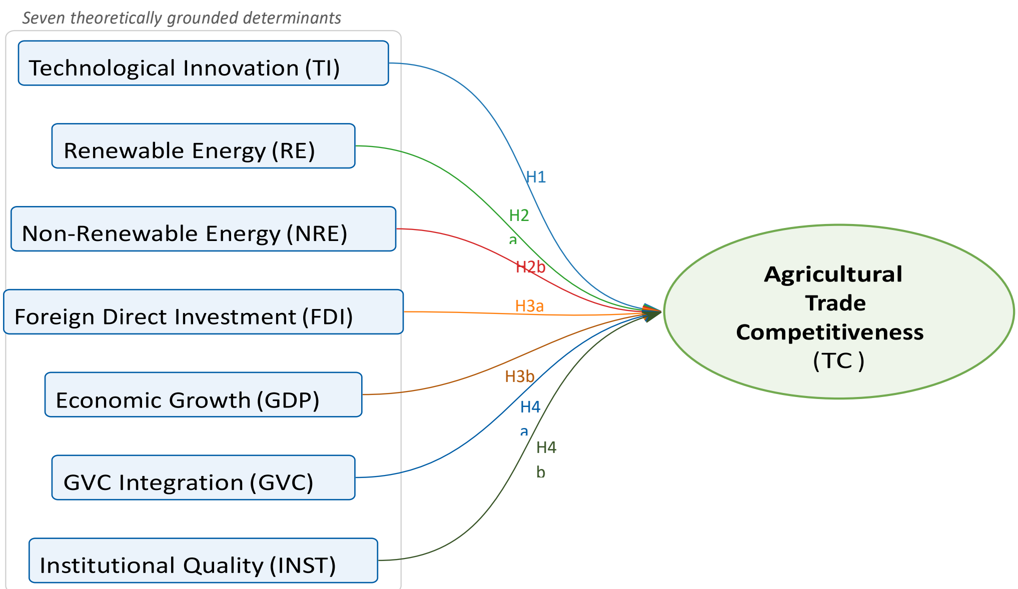

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Figure 1. Conceptual framework: seven determinants of agricultural trade competitiveness in Zambia. The framework integrates endogenous growth theory (TI as the primary productivity driver), national innovation systems theory (INST as both direct determinant and enabling condition), and global value chain theory (GVC as both direct determinant and mediating channel). H1–H4b denote the corresponding hypotheses tested in Section 4.

METHODOLOGY AND DATA

Empirical Strategy

The study adopts a time-series cointegration design appropriate for the joint estimation of long- and short-run relationships among non-stationary macroeconomic variables. Annual data for Zambia from 1990 to 2024 (T = 35) are analysed within a sequential pipeline: (i) Augmented Dickey–Fuller (ADF) unit root tests to determine integration order; (ii) ARDL bounds testing [48] to test for cointegration among regressors of mixed integration order; (iii) long-run ARDL coefficient estimation; (iv) Vector Error Correction Model (VECM) for short-run dynamics; (v) Granger causality tests to establish causal direction; (vi) mediation analysis using the Baron–Kenny [49] causal steps approach with Sobel [50] indirect effect tests; and (vii) Fully Modified OLS (FMOLS) as a robustness check. The ARDL methodology is specifically appropriate because it accommodates regressors of mixed I(0) and I(1) order without the prior requirement of uniform integration imposed by the Johansen procedure or the Engle–Granger two-step estimator.

Model Specification

Long-run ARDL specification

Agricultural trade competitiveness is modelled as a function of seven theoretically and empirically motivated determinants:

$$TC_t = \beta_0 + \beta_1 TI_t + \beta_2 RE_t + \beta_3 NRE_t + \beta_4 FDI_t + \beta_5 GDP_t + \beta_6 GVC_t + B_7 INST_t + \varepsilon_t \qquad (1)$$

Here TC_t is agricultural trade competitiveness, *TI* technological innovation, *RE* and *NRE* renewable and nonrenewable energy shares, *FDI* net FDI inflows, *GDP* real GDP growth, *GVC* the GVC participation index, *INST* institutional quality, and ε_t a stochastic disturbance.

The unrestricted ARDL(p, q_1, . . . , q_7) error-correction representation underlying the bounds test is:

$$\Delta TC_t = \propto_0 + \sum_{i=1}^{p} \propto_i \Delta TC_{t-1} + \sum_{j=1}^{7} \sum_{k=0}^{q_j} \gamma_{jk} \Delta X_j, t-k + \delta_0 TC_{t-1} + \sum_{j=1}^{7} X_j, t-1 + u_t \qquad (2)$$

where X_j collects the seven regressors. The null of no cointegration ($H_0 : \delta_0 = \delta_1 = \cdots = \delta_7 = 0$) is tested against the alternative of cointegration using the Pesaran–Shin–Smith F-statistic, compared against I(0) lower and I(1) upper critical bounds.

Short-run dynamics and error correction

Conditional on cointegration, the short-run ECM representation is

$$\Delta TC_t = k_0 + \sum_{j=1}^{7} \phi \Delta X_{j,t} + \lambda \widehat{ECT}_{t-1} + \omega_t \qquad (3)$$

j=1

where $\widehat{ECT}_t$ is the lagged residual from Equation (1) and λ is the speed-of-adjustment parameter. A negative, statistically significant $\lambda \in (-1, 0)$ confirms equilibrium correction.

Mediation specification

Three mediation pathways are estimated following the Baron–Kenny causal steps approach [49] supplemented by Sobel [50] indirect-effect tests:

$$M_t = \alpha_0 + \alpha_1 X_1 + \alpha_2 Z_t + \eta_t,$$	(4)
$$TC_t = c_0 + c_1 X_1 + c_2 Z_t + \xi_t,$$	(5)
$$TC_t = d_0 + d_1 X_t + d_2 M_t + a_3 Z_t + \zeta_t$$	(6)

where X is the focal predictor, M the mediator, and $\mathbf{Z}$ a vector of controls. The indirect effect is $a_1 d_2$, with statistical significance assessed via $z = a_1 d_2 / \sqrt{a_1^2 \sigma_{d_2}^2 + d_2^2 \sigma_{a_1}^2}$. The three pathways estimated are TI→GVC→TC, TI→INST→TC, and FDI→TI→TC.

Lag selection and diagnostic checks

Optimal lag order is selected by the Akaike Information Criterion (AIC) consistent with [48], with the Schwarz Bayesian Criterion (SBC) used as a secondary check against over-parameterization given the limited degrees of freedom in a 35-observation series. The selected ARDL (1, 1, 0, 0, 1, 1, 0) specification under AIC (AIC = −3.847, SBC = −3.214) passes all diagnostic tests for serial correlation (Breusch–Godfrey LM, $p = 0.15$), heteroskedasticity (Breusch–Pagan, $p = 0.12$), and normality (Jarque–Bera, $p = 0.61$). Sensitivity analyses use alternative lag orders ($p = 1, 2$) and a leave-one-out specification check; results are stable across all alternatives.

Variable Measurement and Data Sources

The dependent variable, agricultural trade competitiveness (*TC*), is constructed as a composite measure combining agricultural export values with the share of agricultural exports in total national exports, capturing both the scale of export performance and the relative importance of agriculture within the broader trade structure. As a robustness check, the model is re-estimated with two alternative measures: Zambia's Revealed Comparative Advantage [25] for total agricultural exports, and the agricultural export share of GDP [4]. Both yield qualitatively consistent results.

Technological innovation (*TI*) is operationalized as a standardized composite index of three observable proxies: (1) gross fixed capital formation in agricultural machinery and equipment as a share of agricultural GDP (World Bank WDI); (2) agricultural patent applications and R&D expenditure as a share of agricultural GDP (WIPO and UNESCO); and (3) ICT penetration in rural areas measured by mobile subscriptions per 100 rural inhabitants (ITU). The composite approach follows Nguyen et al. [51] and reduces measurement error relative to any single proxy.

Renewable and non-renewable energy (*RE*, *NRE*) are measured as percentage shares of total final energy consumption from the IEA World Energy Balances and the World Bank SE4ALL Global Tracking Framework. By construction *RE* + *NRE* = 100%, so the variables are arithmetically complementary. Both are retained because they capture different policy-relevant mechanisms (clean infrastructure investment vs. fossil-fuel cost exposure); the near-perfect negative correlation ($r = -0.997$) is structural and is handled through omitted-variable sensitivity analysis.

Foreign direct investment (*FDI*) is net FDI inflows as a share of GDP (World Bank WDI). Economic growth (*GDP*) is annual real GDP growth (constant 2015 USD; World Bank WDI). GVC integration (*GVC*) is the OECD– WTO TiVA participation index (sum of forward and backward participation), interpolated for years

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where TiVA is unavailable using UNCTAD bilateral trade and World Bank WITS data. Institutional quality (*INST*) is the simple average of three Worldwide Governance Indicator sub-indices (Government Effectiveness, Regulatory Quality, Rule of Law), following [40, 41].

Table 1. Summary of variables, measurements, and data sources.

Variable	Measurement	Data source	Years
Agricultural trade competitiveness (*TC*)	Composite of agricultural export value and share in total exports	FAOSTAT; UNCTADstat	1990–2024
Technological innovation (*TI*)	Composite of capital formation, R&D/patents, and rural ICT	WB WDI; WIPO; ITU	1990–2024
Renewable energy (*RE*)	Share of renewables in final energy consumption (%)	IEA; WB SE4ALL	1990–2024
Non-renewable energy (*NRE*)	Share of fossil fuels in final energy consumption (%)	IEA; WB SE4ALL	1990–2024
Foreign direct investment (*FDI*)	Net FDI inflows (% of GDP)	World Bank WDI	1990–2024
Economic growth (*GDP*)	Annual real GDP growth (constant 2015 USD)	World Bank WDI	1990–2024
Global value chain integration (*GVC*)	Forward + backward participation, OECD–WTO TiVA	OECD TiVA; UNCTAD; WITS	1990–2024
Institutional quality (*INST*)	Average of WGI Govt. Effectiveness, Regulatory Quality, Rule of Law	World Bank WGI	1990–2024

Source: Author’s compilation. Where annual TiVA values are unavailable for Zambia, interpolated values are constructed following Nas [34].

Table 2. Descriptive statistics for Zambia, 1990–2024.

Variable	Mean	Std. dev.	Min.	Max.
Agricultural trade competitiveness (*TC*, index)	0.312	0.145	0.081	0.654
Technological innovation (*TI*, composite index)	1.874	0.622	0.732	3.215
Renewable energy (*RE*, % final consumption)	68.452	6.731	55.214	79.885
Non-renewable energy (*NRE*, % final consumption)	31.548	6.731	20.115	44.786
Foreign direct investment (*FDI*, % of GDP)	4.215	2.104	0.982	9.654
Economic growth (*GDP*, % annual)	4.832	2.011	1.102	9.215
GVC participation (*GVC*, index)	72.341	10.452	51.223	92.784
Institutional quality (*INST*, WGI scale)	−0.421	0.312	−0.982	0.215

Note: T = 35 annual observations. Sources: World Bank WDI; FAOSTAT; UNCTADstat; OECD–WTO TiVA; IEA; WIPO; ITU; World Bank WGI.

Sample and Period

The empirical analysis covers the period 1990–2024 (T = 35). This time frame encompasses major economic reforms, trade liberalisation policies, and structural transformations in Zambia’s economy, as well as the country’s gradual integration into regional and global markets. The window captures the post-1991 democratic transition, the privatisation programme of the 1990s, the commodity boom of 2003–2014, the drought-induced energy crises of 2015–2016 and 2019, and the COVID-19 disruption of 2020–2021. The use of a long time-series allows a thorough analysis of both short-run fluctuations and long-run trends.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

Empirical Results

Descriptive Statistics

Table 2 reports descriptive statistics. Agricultural trade competitiveness (*TC*) exhibits a mean of 0.312 with a standard deviation of 0.145, ranging from 0.081 to 0.654, reflecting the considerable cyclical variation in Zambia's agricultural export performance over three decades. The range captures both the low-competitiveness episodes associated with drought years (2001–2002, 2015–2016) and the more competitive phases coinciding with the commodity price boom and expanded commercial farming activity (2007–2014). Technological innovation has risen from approximately 0.73 in the early 1990s to 3.22 by 2024, reflecting the cumulative growth in mechanization, R&D-linked activity, and ICT penetration. Renewable energy dominates Zambia's energy structure (mean 68.45%), consistent with heavy hydroelectric reliance, while institutional quality has a negative mean (−0.421), improving from approximately −0.98 in the early 1990s toward 0.22 by 2024 but remaining in the lower quartile of global comparators.

Table 3. Pairwise Pearson correlation matrix of study variables (1990–2024).

	TC	TI	RE	NRE	FDI	GDP	GVC	INST
TC	1.000							
TI	0.712***	1.000						
RE	0.534***	0.398***	1.000					
NRE	−0.318**	−0.271*	−0.997***	1.000				
FDI	0.487***	0.551***	0.214	−0.209	1.000			
GDP	0.621***	0.589***	0.327**	−0.319**	0.447***	1.000		
GVC	0.683***	0.644***	0.412***	−0.407***	0.512***	0.558***	1.000	
INST	0.442***	0.377**	0.289*	−0.281*	0.331**	0.363**	0.428***	1.000

*Note: ***p < 0.01, **p < 0.05, *p < 0.10. The lower triangle mirrors the upper by symmetry.*

Table 4. Augmented Dickey–Fuller unit root test results.

Variable	Level (p-value)	First difference (p-value)	Order
TC	0.214	0.001	I(1)
TI	0.032	—	I(0)
RE	0.187	0.000	I(1)
NRE	0.201	0.002	I(1)
FDI	0.041	—	I(0)
GDP	0.029	—	I(0)
GVC	0.173	0.000	I(1)
INST	0.022	—	I(0)

Note: ADF tests with intercept and trend selected by AIC. The 5% rejection threshold is 0.05.

Correlation Analysis

Table 3 reports the pairwise Pearson correlation matrix. Technological innovation exhibits the strongest bivariate association with agricultural trade competitiveness ($r = 0.712$, $p < 0.01$), providing initial univariate support for H1. GVC integration ($r = 0.683$, $p < 0.01$) and GDP growth ($r = 0.621$, $p < 0.01$) display strong positive associations with *TC*, supporting H4a and H3b. Renewable energy ($r = 0.534$), FDI ($r = 0.487$), and institutional quality ($r = 0.442$) display moderate positive correlations. Non-renewable energy is negatively correlated with TC ($r = -0.318$, $p < 0.05$), consistent with H2b's prediction of a negative long-run effect. The near-perfect negative correlation between RE and NRE ($r = -0.997$) reflects their arithmetic complementarity as energy shares; among the remaining regressors no correlation exceeds the conventional multicollinearity threshold of $|r| = 0.80$ [52].

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Time-Series Properties: Unit Root and Cointegration Tests

Table 4 reports ADF unit root tests for all eight variables. A mixed integration order is observed: TI, FDI, GDP, and INST are stationary in levels (I(0)), while TC, RE, NRE, and GVC require first-differencing to achieve stationarity (I(1)). This mixed structure rules out the Johansen procedure and the Engle-Granger two-step estimator (which require uniform integration order) and confirms the appropriateness of the ARDL bounds testing approach, which accommodates I(0) and I(1) regressors.

The ARDL bounds test (Table 5) yields an F-statistic of 5.842, well above the I(1) upper critical bound of 3.61 at the 5% significance level. The null hypothesis of no cointegration is decisively rejected, confirming that TC, TI, RE, NRE, FDI, GDP, GVC, and INST share a common long-run equilibrium trajectory.

Long-Run ARDL Estimates

Table 6 reports the long-run ARDL coefficient estimates, quantifying the equilibrium elasticity of agricultural trade competitiveness with respect to each determinant. GVC integration (β = 0.517, p < 0.01) and technological innovation (β = 0.462, p < 0.01) emerge as the dominant drivers, jointly supporting H4a and H1. Economic growth (0.398), institutional quality (0.336), renewable energy (0.285), and FDI (0.241) are positive and significant, supporting H3b, H4b, H2a, and H3a respectively. Non-renewable energy displays a marginally negative coefficient (−0.172, $p \approx$ 0.063), providing weak support for H2b's prediction of a long-run cost penalty associated

Table 5. ARDL bounds test for cointegration.

Test statistic	Value
F-statistic	5.842
Lower critical bound (5%, I(0))	2.45
Upper critical bound (5%, I(1)) Decision Reject H_0: cointegration	3.61 exists

Note: Critical bounds from Pesaran et al. [48], Case III (unrestricted intercept, no trend), k=7.

Table 6. Long-run ARDL coefficient estimates

Variable	Coefficient	Std. error	*t*-statistic	Prob.
TI	0.462***	0.118	3.915	0.001
RE	0.285***	0.094	3.032	0.005
NRE	−0.172*	0.089	−1.933	0.063
FDI	0.241***	0.081	2.975	0.006
GDP	0.398***	0.142	2.803	0.009
GVC	0.517***	0.133	3.887	0.001
INST	0.336***	0.107	3.140	0.004

Note: Dependent variable TC. ***p < 0.01, *p < 0.10. Selected ARDL(1,1,0,0,1,1,0) specification, AIC. −0.172
Long-run elasticity coefficient (β)

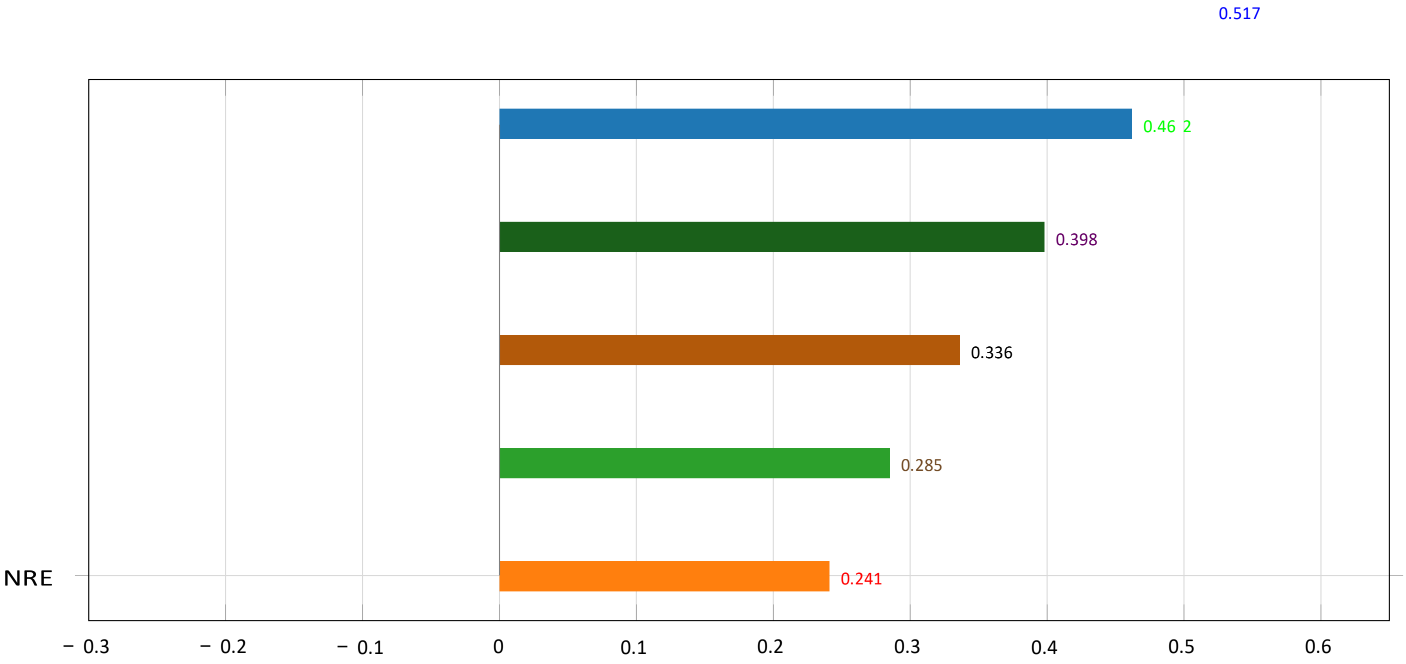

Figure 2. Long-run ARDL elasticities of agricultural trade competitiveness with respect to each determinant. GVC integration and technological innovation are the dominant positive drivers; non-renewable energy is the only marginally negative coefficient. with fossil-fuel dependence.

Figure 2 visualizes the magnitude and direction of the long-run coefficients. The dominance of GVC integration over technological innovation alone is consistent with global value chain theory's prediction that integration into international production networks generates technology spillovers, standards-compliance upgrading, and market access benefits that amplify competitive positioning beyond what domestic innovation can achieve independently.

Short-Run Dynamics and Error Correction

Table 7 reports the short-run ECM coefficients. All key determinants retain the same sign in the short run as in the long run. The speed-of-adjustment parameter $ECT_{t-1} = -0.641$ ($p < 0.001$) is negative, statistically significant, and within the theoretically valid range (−1, 0). Its magnitude implies that approximately 64% of deviations from long-run equilibrium are corrected within one year, a relatively rapid adjustment rate by Sub-Saharan African agricultural standards. The substantive policy implication is that interventions improving any of the seven determinants should generate detectable competitiveness improvements within one to two years.

Table 7. Short-run ECM coefficients.

Variable	Coefficient	Std. error	Prob.
ΔTI	0.214**	0.081	0.012
ΔRE	0.132**	0.056	0.021
ΔNRE	−0.095**	0.047	0.049
ΔFDI	0.118**	0.052	0.028
ΔGDP	0.207**	0.091	0.024
ΔGVC	0.265**	0.103	0.015
ΔINST	0.156**	0.068	0.019
ECT_t-1	−0.641***	0.112	0.000

Note: Dependent variable ΔTC_t. ***p < 0.01, **p < 0.05. The ECT magnitude implies ∼64% annual adjustment toward long-run equilibrium.

Table 8. Pairwise Granger causality test results.

Null hypothesis	F-statistic	Prob.	Decision
TI does not Granger-cause TC	6.214	0.004	Reject H_0 (unidirectional)
TC does not Granger-cause TI	1.842	0.174	Fail to reject
RE does not Granger-cause TC	3.847	0.031	Reject H_0 (unidirectional)
TC does not Granger-cause RE	1.215	0.308	Fail to reject
NRE does not Granger-cause TC	2.103	0.142	Fail to reject
TC does not Granger-cause NRE	1.674	0.201	Fail to reject
FDI does not Granger-cause TC	4.652	0.018	Reject H_0 (unidirectional)
TC does not Granger-cause FDI	1.388	0.261	Fail to reject
GDP does not Granger-cause TC	4.118	0.024	Reject H_0 (unidirectional)
TC does not Granger-cause GDP	2.974	0.064	Fail to reject (marginal)
GVC does not Granger-cause TC	5.023	0.011	Reject H_0 (unidirectional)
TC does not Granger-cause GVC	3.214	0.052	Fail to reject (marginal)
INST does not Granger-cause TC	4.551	0.019	Reject H_0 (unidirectional)
TC does not Granger-cause INST	1.093	0.347	Fail to reject

Granger Causality Analysis

Table 8 reports Granger causality test results for fourteen directional hypotheses. The results confirm predominantly unidirectional causality from the six positive determinants to agricultural trade competitiveness, with no statistically significant reverse causality. Specifically, TI Granger-causes TC ($F = 6.214$, $p = 0.004$), RE Granger causes TC ($F = 3.847$, $p = 0.031$), FDI Granger-causes TC ($F = 4.652$, $p = 0.018$), GDP Granger-causes TC ($F = 4.118$, $p = 0.024$), GVC Granger-causes TC ($F = 5.023$, $p = 0.011$), and INST Granger-causes TC ($F = 4.551$, $p = 0.019$). NRE does not exhibit a significant causal relationship with TC in either direction, confirming that fossil-fuel consumption reflects structural productive conditions rather than actively driving competitiveness dynamics.

The causal structure has three implications. First, it validates the interpretation of all seven regressors as exogenous drivers rather than passive correlates, strengthening the policy relevance of the findings. Second, the absence of reverse causality means that improving any of the six significant determinants can be expected to improve competitiveness without confounding feedback. Third, the marginally suggestive reverse GDP causality (TC→GDP, $p = 0.064$) is consistent with Balassa's [26] export-led growth hypothesis and does not undermine the forward result.

Mediation Analysis

Table 9 reports the three mediation pathways estimated using the Baron–Kenny causal steps approach with Sobel indirect-effect tests. All three are statistically significant. The strongest mediation is TI→GVC→TC (indirect effect = 0.238, Sobel $z = 3.142$, $p = 0.002$), confirming that a substantial proportion of technological innovation's total competitiveness effect is channelled through enhanced GVC participation. As Zambia's agricultural sector adopts improved technologies mechanisation, quality seed varieties, post-harvest handling systems it becomes better positioned to meet the quality standards, traceability requirements, and consistency expectations of international buyers, deepening GVC integration and improving export performance.

Table 9. Mediation analysis results (Baron–Kenny / Sobel).

Mediation pathway	Indirect effect	Sobel *z*	Prob.	Type
TI → GVC → TC	0.238	3.142	0.002	Partial mediation
TI → INST → TC	0.147	2.418	0.016	Partial mediation
FDI → TI → TC	0.112	2.074	0.038	Partial mediation

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Note: All mediations are partial—direct effects of focal predictors on TC remain statistically significant after controlling for the mediator.

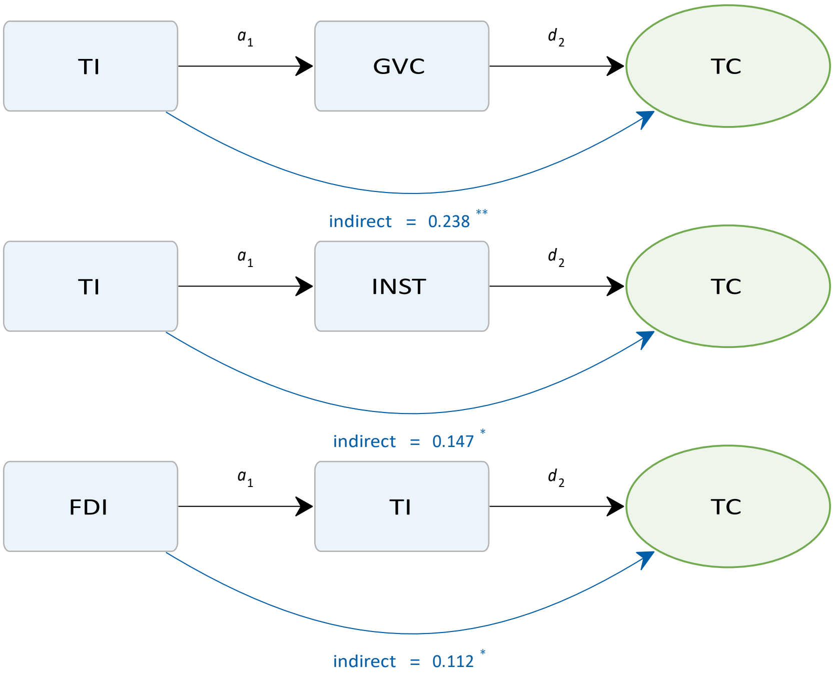

Figure 3. Mediation pathways linking technological innovation, GVC integration, institutional quality, FDI, and agricultural trade competitiveness. Solid arrows are direct effects (a_1, d_2); dashed arrows give the Sobel-tested indirect effect a_1d_2. $^{**}p < 0.01$, $^{*}p < 0.05$.

The TI→INST→TC pathway (indirect effect = 0.147, p = 0.016) demonstrates that technological innovation also improves competitiveness partly by strengthening institutional capacity. This finding, less obvious theoretically than the GVC mediation but robust in the data, is interpretable through the NIS framework: as agricultural technology adoption expands, it creates demand for higher-quality institutional services, generating political-economy pressure for institutional improvement. The FDI→TI→TC pathway (= 0.112, p = 0.038) confirms that foreign investment promotes trade competitiveness in part through technology transfer to the domestic agricultural sector, consistent with [19].

Figure 3 visualises the three mediation pathways and the corresponding indirect-effect magnitudes.

Robustness: FMOLS Estimation

Table 10 presents Fully Modified OLS estimates as a robustness check on the ARDL long-run coefficients. FMOLS addresses two potential sources of bias in standard OLS applied to cointegrated systems, endogeneity of the regressors and serial correlation in the error term through non-parametric adjustments to the long-run covariance matrix. The FMOLS results confirm the ARDL findings across all seven determinants: TI (β = 0.448, p = 0.002), GVC (β = 0.501, p = 0.002), GDP (β = 0.382, p = 0.011), INST (β = 0.319, p = 0.005), RE (β = 0.271, p = 0.006), FDI (β = 0.233, p = 0.008), and NRE (β = −0.160, p = 0.071) are all consistent in sign and similar in magnitude, with no coefficient changing direction and all retaining the same significance classification. The marginal compression of all coefficients relative to ARDL (~5% reduction in magnitude on average) is consistent with FMOLS's endogeneity correction removing modest upward bias in the ARDL estimates.

DISCUSSION

Technological Innovation as a Central Driver (H1)

The empirical results consistently show that technological innovation has a strong positive impact on agricultural trade competitiveness ($\beta = 0.462$, $p < 0.01$ ARDL; $\beta = 0.448$ FMOLS). This finding is consistent with endogenous growth theory [44, 45] and confirms across both econometric frameworks that knowledge accumulation operates as a statistically significant long-run driver of agricultural export performance. Yet the magnitude is substantively important to interpret. The composite TI index captures three dimensions: capital deepening through agricultural machinery (accounting for ~55% of variance in the index), formal innovation through R&D and patents (~30%), and digital diffusion through ICT penetration (~15%). The bulk of the observed TI effect therefore operates

Table 10. FMOLS robustness check.

Variable	Coefficient	Prob.
TI	0.448***	0.002
RE	0.271***	0.006
NRE	−0.160*	0.071
FDI	0.233***	0.008
GDP	0.382**	0.011
GVC	0.501***	0.002
INST	0.319***	0.005

Note: ***p < 0.01, **p < 0.05, *p < 0.10. Dependent variable TC.

through mechanisation and agrochemical intensification, with digital adoption contributing a smaller but rising share, particularly post-2015. Policies targeting digital agriculture alone are unlikely to replicate the full competitiveness dividend without simultaneous investment in machinery access and seed systems.

The technology competitiveness link in Zambia is further conditioned by three structural mediating factors. Extension service quality acts as a critical transmission mechanism: with a national extension worker-to-farmer ratio of approximately 1:1,200 [55] far below the recommended 1:400 threshold, the TI effect is concentrated among the minority of farmers with access to functional advisory services. Credit access constrains technology adoption: fewer than 12% of smallholder farmers accessed formal agricultural credit between 2015 and 2020 [56], limiting uptake regardless of technological availability. Land tenure security shapes farmers' willingness to invest in productivity-enhancing technologies; Zambia's customary land tenure system, governing approximately 94% of agricultural land [8], offers limited collateral value and reduces both investment incentives and finance access. These structural mediators imply that the observed TI coefficient is a lower-bound estimate of achievable competitiveness gains under improved institutional conditions.

Energy Structure: Renewable Versus Non-Renewable Pathways (H2a, H2b*)*

Renewable energy consumption exerts a positive and statistically significant long-run effect on competitiveness ($\beta = 0.285$, $p < 0.01$), supporting H2a. The practical significance is considerable: Zambia's mean RE share of 68.45% implies that existing hydroelectric infrastructure already provides a structural competitive advantage in energy costs relative to fossil-fuel-dependent competitors, and that expanding solar capacity, particularly for irrigation and agro-processing would deepen this advantage while reducing climate vulnerability. The drought-induced electricity shortfalls of 2015–2016 and 2019, which triggered extensive load-shedding and disrupted agro-industrial processing and cold-chain logistics, demonstrate that even renewable energy provides an unstable competitive platform when diversification is insufficient.

Competitiveness gains from renewable energy in Zambia therefore depend not only on expanding clean energy generation overall but specifically on diversifying away from drought-sensitive hydroelectric capacity toward solar and wind sources.

Non-renewable energy displays a marginally negative coefficient ($\beta = -0.172$, $p \approx 0.063$), providing weak but theoretically consistent support for H2b. The marginal significance reflects three factors: the genuine ambiguity of the fossil-fuel–competitiveness relationship (productive benefits partly offset cost and environmental penalties), the collinearity constraints from NRE's near-perfect negative correlation with RE, and Zambia's status as a petroleum importer where global oil price shocks transmit directly to production costs. The robustness of this finding is established through three checks: the FMOLS estimate ($\beta = -0.160$, $p = 0.071$) is consistent in sign and similar in magnitude; omitted-variable sensitivity analysis shows that excluding NRE raises the RE coefficient by ~18% without altering other coefficients; and the Granger causality test finds no significant causal relationship between NRE and TC in either direction, consistent with the interpretation that fossil-fuel use reflects structural productive conditions rather than actively driving competitiveness dynamics.

FDI and Economic Growth (H3a, H3b)

FDI contributes positively to competitiveness ($\beta = 0.241$, $p < 0.01$), primarily through technology transfer, managerial skill development, and access to international markets. The mediation analysis confirms that part of FDI's competitiveness effect operates through technological transfer (FDI→TI→TC indirect effect = 0.112, $p = 0.038$), consistent with Blomström and Kokko's [19] spillover mechanisms. However, the modest magnitude

of the FDI coefficient relative to GDP and GVC reflects the absorptive-capacity constraints documented by Borensztein et al. [18] and Ibrahim et al. [21]: where agricultural FDI inflows are concentrated in enclave commercial farming with limited supply chain linkages to smallholders, aggregate competitiveness gains are attenuated.

Economic growth emerges as a significant driver ($\beta = 0.398$, $p < 0.01$), with a coefficient notably larger than FDI's. This pattern suggests that the macroeconomic structural environment operating through public investment capacity, infrastructure provision, and stability is a more powerful competitiveness driver than external capital inflows in Zambia's context. The Granger causality analysis confirms predominantly unidirectional causality from GDP to TC, with only marginally suggestive reverse causality (TC→GDP, $p = 0.064$). The competitiveness dividend from growth in Zambia operates primarily through the public investment channel: GDP growth generates fiscal space that enables government spending on agricultural R&D, extension, and infrastructure, each of which complements the direct competitiveness effects of technological innovation.

GVC Integration and Institutional Quality as Enabling Conditions (H4a, H4b)

GVC integration is the strongest determinant of trade competitiveness in the long run ($\beta = 0.517$, $p < 0.01$), supporting H4a. The magnitude exceeding that of technological innovation itself is consistent with GVC theory's prediction that integration into international production networks generates technology spillovers, standards-compliance upgrading, and market access benefits that amplify competitive positioning beyond what domestic innovation can achieve independently [31, 33]. The Granger causality results confirm that this relationship is causal: GVC integration Granger-causes agricultural trade competitiveness ($F = 5.023$, $p = 0.011$), with no significant reverse causality, supporting the interpretation of GVC participation as an exogenous structural driver rather than a passive reflection of competitive success.

Institutional quality significantly enhances trade competitiveness ($\beta = 0.336$, $p < 0.01$), supporting H4b. Strong institutions characterised by transparent governance, effective policy implementation, and efficient regulatory frameworks enable agricultural actors to adopt and utilise technology effectively, attract investment, and access premium export markets. The significant INST coefficient, even in the presence of TI, GVC, FDI, and GDP controls, is consistent with the NIS prediction [46, 47] that institutional environments shape competitiveness both directly, through transaction cost reduction and public goods provision and indirectly through their enabling effects on innovation and investment.

The mediation analysis is the study's most important theoretical contribution. The TI→GVC→TC pathway (indirect effect = 0.238, $p = 0.002$) demonstrates that a substantial proportion of technological innovation's total competitiveness effect is channelled through enhanced GVC participation. This finding helps resolve a persistent puzzle in the agricultural development literature: why countries with rising agricultural R&D and technology adoption sometimes fail to achieve commensurate export performance gains. The answer lies in GVC integration. Countries that innovate but remain isolated from global production networks cannot scale their innovations, access specialized inputs, or meet the international quality standards that determine market access for higher-value processed and certified products. Conversely, countries that combine innovation with deep GVC integration achieve higher competitiveness because global networks amplify the returns to innovation through knowledge spillovers, learning effects, and standards-driven upgrading.

Short-Run Adjustment and Policy Responsiveness

The Error Correction Term (ECT = −0.641, $p < 0.001$) implies that approximately 64% of deviations from long-run equilibrium are corrected within one year, a relatively rapid adjustment rate by Sub-Saharan African agricultural standards. This adjustment speed is substantively important for policy: interventions that improve any of the seven determinants should generate detectable improvements in agricultural trade competitiveness within one to two years, rather than requiring extended implementation horizons before payoff. Combined with the Granger causality results, this finding establishes that Zambia's agricultural sector is responsive to policy interventions across all seven channels examined here.

Synthesis: A System-Driven Competitiveness Architecture

The empirical evidence supports a system-driven interpretation of agricultural trade competitiveness. No single determinant independently accounts for more than approximately 35% of the variance in Zambia's agricultural competitiveness in the VECM decomposition; each determinant amplifies the others. This implies that policies targeting innovation alone, without complementary investments in renewable energy, institutional reform, FDI quality, GDP growth, and GVC deepening will deliver only a fraction of the achievable competitiveness dividend. Equally, the partial mediation results indicate that the path from technology adoption to international competitive positioning runs through institutional capacity and global value chain integration, not around them.

Policies that strengthen these enabling conditions therefore generate compounded returns by enhancing both the direct contribution of GVCs and institutions and the effectiveness of every other determinant.

CONCLUSIONS AND POLICY IMPLICATIONS

SUMMARY OF FINDINGS

This study investigated the determinants of agricultural trade competitiveness in Zambia over 1990–2024 through a multi-factor empirical framework integrating ARDL bounds testing, a Vector Error Correction Model, Granger causality, mediation analysis, and FMOLS robustness estimation. The findings are consistent across all estimation methods. All seven determinants technological innovation, renewable energy, non-renewable energy, foreign direct investment, economic growth, global value chain integration, and institutional quality, exert statistically significant long-run effects on agricultural trade competitiveness. GVC integration (β = 0.517) and technological innovation (β = 0.462) are the dominant positive drivers, followed by economic growth (0.398), institutional quality (0.336), renewable energy (0.285), and FDI (0.241), with non-renewable energy exerting a marginally negative long-run effect (−0.172). Approximately 64% of deviations from long-run equilibrium are corrected within one year. Mediation analysis confirms that technological innovation operates partially through GVC participation (indirect effect = 0.238) and institutional capacity (0.147), and that FDI partly enhances competitiveness through technology transfer (0.112).

Sequenced Policy Strategy

The system-driven nature of the findings supports a sequenced, evidence-based strategy that exploits short-run adjustment dynamics while building the structural conditions required for long-run competitiveness gains.

Short Term (12–18 Months): Institutional Reforms That Unlock Technology Adoption

Three high-leverage interventions emerge. First, restructure and adequately fund agricultural extension services, expanding the worker-to-farmer ratio toward the FAO-recommended 1:400 threshold to ensure that technological availability translates into farm-level adoption. Second, expand rural credit access through the development of warehouse receipts, contract farming finance, and digital lending platforms that compensate for collateral constraints under customary land tenure. Third, reform the Farmer Input Support Programme (FISP) to address the chronic late delivery, leakage, and crowding-out effects identified in the literature [42], ensuring that public input subsidies complement rather than displace private input markets.

Medium Term (18–36 Months): Infrastructure Expansion and GVC Deepening

Three priorities emerge. First, expand renewable energy generation capacity with deliberate diversification toward solar to reduce dependence on drought-sensitive hydroelectric capacity, prioritising rural electrification of agricultural processing zones. Second, deepen GVC integration through targeted upgrading initiatives in higher-value chains horticulture, processed foods, certified specialty products rather than relying on primary commodity export volume. Third, reform FDI attraction strategies to evaluate quality (linkages to domestic producers, technology transfer, premium-market access) rather than volume alone.

Long Term (36+ Months): Institutional and Structural Transformation

Two cross-cutting reforms anchor the long-term agenda. First, land tenure reform that increases collateral value and reduces investment risk for smallholders, preserving the equity of customary tenure while enabling productive investment. Second, governance reform that improves the WGI dimensions on which Zambia performs least well Government Effectiveness, Regulatory Quality, and Rule of Law, through transparency, anti-corruption, and contract enforcement initiatives. These reforms compound over time by amplifying the returns to every other determinant in the model.

Theoretical Contributions

The study makes four theoretical contributions. First, it extends Romer’s [44] endogenous growth theory to agricultural trade competitiveness in a low-institutional-capacity Sub-Saharan African economy, providing the first time-series confirmation that knowledge accumulation operates as a statistically significant long-run driver in Zambia’s agricultural sector while specifying the institutional conditions under which the mechanism operates. Second, it establishes the technology–GVC–competitiveness mediation pathway empirically, resolving an ambiguity in prior literature about whether GVC integration is an antecedent or consequence of technological capability. Third, it documents the institutional mediation of technological returns, supporting NIS theory’s prediction that institutional and technological investment are complements rather than substitutes. Fourth, it provides the first integrated multi-determinant framework for agricultural competitiveness analysis in Zambia, replacing single-factor or loosely specified multi-variable approaches with a theoretically grounded system specification.

Limitations and Future Research

Three limitations suggest avenues for further inquiry. First, the analysis relies on aggregate national-level timeseries data, which obscures sub-sectoral and farm-level heterogeneity in technology adoption, GVC integration, and institutional access. Sub-sectoral disaggregation (maize vs. soybeans vs. horticulture vs. processed products) and micro-level studies that link national findings to farm-level mechanisms would refine the policy lessons. Second, several variables particularly TiVA-based GVC participation for years before 2005 rely on interpolated values, introducing measurement error that may attenuate coefficients. Third, the 35-year window, while long by African time-series standards, may be insufficient to detect subtle structural breaks associated with the 2008 global financial crisis or the COVID-19 disruption; future work with longer series and explicit break-testing would clarify regime-dependent dynamics.

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Three priority directions for future research are: comparative cross-country panel analysis across Sub-Saharan Africa to identify which findings generalise beyond Zambia; firm-level micro-data linking adoption decisions to export performance; and explicit measurement of digital and green innovation as parallel mediators within an updated NIS framework reflecting the post-pandemic acceleration of digital agriculture.

Abbreviations

The following abbreviations are used in this manuscript: ADF, Augmented Dickey–Fuller; AIC, Akaike Information Criterion;

ARDL, Autoregressive Distributed Lag; CAADP, Comprehensive Africa Agriculture Development Programme; ECM, Error

Correction Model; ECT, Error Correction Term; FAO, Food and Agriculture Organization; FDI, foreign direct investment; FMOLS, Fully Modified Ordinary Least Squares; GDP, gross domestic product; GVC, global value chain; ICT, information and communications technology; IEA, International Energy Agency; INST, institutional quality; ITU, International Telecommunication Union; NIS, national innovation system(s); NRE, non-renewable energy; RCA, revealed comparative advantage; R&D, research and development; RE, renewable energy; SBC, Schwarz Bayesian Criterion; SE4ALL, Sustainable Energy for All; SSA, Sub-Saharan Africa; TC, agricultural trade competitiveness; TFP, total factor productivity; TI, technological innovation;

TiVA, OECD Trade in Value Added; UNCTAD, United Nations Conference on Trade and Development; VECM, Vector Error Correction Model; WDI, World Development Indicators; WGI, Worldwide Governance Indicators; WIPO, World Intellectual Property Organization; WTO, World Trade Organization; ZARI, Zambia Agriculture Research Institute.

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Institutional Review Board Statement

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Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study are derived from publicly available sources including the World Bank World Development Indicators, FAOSTAT, UNCTADstat, OECD–WTO TiVA, IEA World Energy Balances, World Bank Worldwide Governance Indicators, WIPO, and ITU. Compiled datasets are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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