The Role of Human Capital Development and Technology Adoption in the Food Security of Sub-Saharan African Countries.

Samuel, David Adebisi[1*], Wale-Odunaiya, Enitan[2]

[1]Department of Economics, Trinity University, Lagos, Nigeria.

[2]Department of Economics, Veritas University, Abuja

***Corresponding Author**

DOI: https://dx.doi.org/10.47772/IJRISS.2025.907000120

Received: 08 May 2025; Accepted: 13 May 2025; Published: 02 August 2025

ABSTRACT

This study examines the impact of human capital development and technological innovation on food security in Sub-Saharan African countries using panel data covering 45 countries from 2000 to 2022. Drawing on the Human Capital Theory, Diffusion of Innovations Theory, and the Sustainable Livelihoods Framework, the study employs the Panel ARDL methodology to assess both short-run and long-run dynamics. Unit root and cointegration tests confirm the appropriateness of the model, while robustness checks, cross-sectional dependence diagnostics, validate the stability of the estimates. The results show that agricultural productivity and government expenditure on education significantly enhance food security in the long run, while technological innovation demonstrates marginal but important influence. The error correction term is negative and significant, indicating a stable long-run relationship among the variables. The study concludes that investments in agricultural education, technology dissemination, and productivity-enhancing initiatives are critical to achieving sustainable food security in the region.

Keywords: Human Capital Development; Technological Innovation; Food Security; Panel ARDL; Sub-Saharan Africa

INTRODUCTION

Food security remains a crucial yet complex issue for African countries. Over the past few decades, food demand in Africa has consistently outpaced supply, leading to persistent food insecurity across the continent. The Food and Agriculture Organization (FAO) estimates that nearly 20% of Africa's population, amounting to over 250 million people, suffers from hunger or malnutrition (FAO, 2021). Factors contributing to this scenario include rapid population growth, environmental challenges such as soil degradation and water scarcity, and economic conditions that impede investment in food production and infrastructure. This situation poses a serious threat to the continent's ability to meet the United Nations' Sustainable Development Goal (SDG) of zero hunger by 2030.

Food security is a multi-dimensional concept that encompasses consistent, equitable access to nutritious and safe food necessary for a healthy life. According to the Food and Agriculture Organization (FAO), food security exists when all people have "physical, social, and economic access to sufficient, safe, and nutritious food" at all times (FAO, 2013). This concept can be understood through four main dimensions: availability, access, utilization, and stability. Food availability focuses on ensuring sufficient food supply through local production and imports, which can be affected by agricultural productivity and market access (FAO, 2013). Access, meanwhile, includes both the physical and economic factors that allow people to obtain food, emphasizing income levels, market infrastructure, and affordability as determinants of whether people can reach and afford food (FAO, 2013). Utilization addresses food safety, nutrition, and the knowledge required for proper dietary intake, recognizing that merely having food is insufficient without safe preparation and proper nutritional knowledge. Lastly, stability ties these dimensions together, ensuring that people have reliable access to food even amid disruptions from economic or environmental shocks, which can be particularly acute in areas susceptible to extreme weather or economic downturns (WFP, 2023). By recognizing these parameters, policymakers can approach food security more effectively, especially in regions like Sub-Saharan Africa, where food systems are under pressure from climate challenges, population growth, and socioeconomic vulnerabilities (WFP, 2023).

Given the mounting pressures on Africa's food systems, human capital development and technology adoption are increasingly recognized as essential drivers of food security and agricultural resilience. Human capital, encompassing the education, skills, health, and overall productivity of a workforce, is a fundamental asset for achieving agricultural growth. In agricultural contexts, human capital directly influences farmers' ability to innovate, adapt to new practices, and efficiently use resources (Ndibe, 2022). Studies, such as Paltasingh & Goyari (2018) reveal that an educated and skilled agricultural workforce is better equipped to adopt modern farming technologies and implement improved agronomic practices. Furthermore, training and education enhance farmers' capacity to make informed decisions, manage resources sustainably, and respond effectively to climate-related risks, all of which are critical for sustainable food production (World Bank, 2014).

Technology adoption in African agriculture refers to the integration of innovative tools, methods, and equipment that can increase productivity, reduce waste, and optimize resource use, such as high-yield crop varieties, precision agriculture technologies, digital farming platforms, and advanced irrigation systems. These technologies hold the potential to transform Africa's agricultural sector by addressing fundamental productivity constraints. For instance, digital platforms enable farmers to access timely information on weather forecasts, pest management, and crop pricing, while mechanization reduces labour intensity and improves efficiency in crop harvesting and soil preparation (Adenle et al, 2019, Cunguara & Darnhofer, 2011).

Despite the promising outlook of human capital and technology adoption for food security, many African countries struggle with severe gaps in education and technology accessibility. Rural areas, where the majority of agricultural activities occur, are often under-resourced, limiting opportunities for farmers to develop their skills and access critical technologies. Moreover, high costs, limited financing options, and insufficient government support hinder the widespread adoption of advanced agricultural technologies (Ruzzante & Bilton, 2021). Thus, while human capital development and technology hold transformative potential, challenges remain that must be addressed through integrated policy frameworks and targeted investments.

The intersection of human capital development, technology adoption, and food security represents a critical frontier in achieving sustainable development in African countries (Adeosun, et al (2024). With its abundant natural resources and significant share of the global agricultural workforce, Africa has considerable potential to become a major player in global food systems. However, food insecurity remains one of the continent's most persistent challenges, aggravated by climate change, population growth, and fragile agricultural systems (Diogo, et al, 2022). Addressing this issue requires a multifaceted approach that encompasses human capital development, technology adoption, and supportive policies.

Human capital development is fundamental to fostering food security. World Bank (2023) expressed it as the accumulation of skills, knowledge, and health that individuals possess, which directly contribute to productivity. In agriculture, human capital is essential for the adoption of sustainable farming practices, efficient use of inputs, and adaptation to changing environmental conditions. It has been established that farmers with higher levels of education and training are more likely to adopt modern agricultural technologies, engage in environmentally sustainable practices, and improve yields (Fadeyi, Ariyawardana & Aziz, 2022). Education and training also improve farmers' ability to interpret market information, make risk-informed decisions, and adapt to evolving technological innovations (J-PAL, 2021).

Technology adoption plays an equally pivotal role (UNCTAD, 2017). Modern technologies, including improved seed varieties, soil sensors, satellite imagery, and mobile-based platforms, have been shown to increase yields, reduce post-harvest losses, and optimize resource use in agricultural production (Doktar, 2023). For instance, precision agriculture technologies help farmers tailor their practices to the specific needs of their crops and land, reducing input costs and enhancing productivity. Mobile technology platforms enable smallholder farmers to access financial services, market prices, and weather updates, which support decision-making and mitigate risks (AUDA-NEPAD, 2023). Despite these benefits, technology adoption in African agriculture remains limited due to barriers such as high initial costs, limited access to credit, and a lack of technical support. These constraints are often more pronounced in rural areas, where poverty and infrastructure deficits are prevalent (Holger et al 2022).

The synergy between human capital development and technology adoption has a significant impact on food security. An educated and skilled workforce is more likely to leverage technological advancements effectively, maximizing productivity and minimizing environmental impacts. As African governments and development organizations work to improve food security, understanding how these two elements: human capital and technology, interact and contribute to agricultural outcomes is crucial. Despite substantial evidence on their importance, there is a knowledge gap concerning the combined effect of human capital and technology on food security outcomes. This study aims to fill that gap by examining the role of human capital and technology in enhancing food security in African countries.

Understanding this relationship has broad implications for policymakers, development practitioners, and agricultural stakeholders. It could guide future investments and initiatives that aim to promote sustainable food systems and economic resilience across the continent. By examining how human capital and technology can complement each other in achieving food security, this study provides insights that are essential for designing effective policies and programs that address the root causes of food insecurity in Africa.

Although substantial investments in agricultural development have been made, food insecurity continues to be a significant challenge in Africa. Many African countries face structural issues such as low literacy rates among farmers, limited access to education in rural areas, and insufficient training programs tailored to modern agricultural practices. These issues are compounded by technology-related challenges, such as limited access to financing for purchasing advanced tools and a lack of technical support for technology deployment (Holger et al 2022).

Moreover, there is limited empirical evidence on how human capital and technology intersect to influence food security outcomes in Africa. This gap hinders the ability of policymakers to make data-driven decisions about where to allocate resources most effectively. Additionally, studies show varying impacts of technology on productivity in the absence of adequate human capital, indicating a need for policies that jointly address educational needs and technological support in agriculture (Boima et al, 2022, Lansana et al, 2021).

While there is extensive research on the benefits of human capital and technology in agriculture globally, there is a shortage of studies specifically focused on Africa. Most studies generalize findings from Asia and Latin America, which may not account for Africa's unique socio-economic and climatic conditions (Fadeyi, Ariyawardana & Aziz, 2022). Many studies do not differentiate between the varying levels of human capital or types of technologies. For instance, digital tools may require different skill sets than mechanized equipment, but few studies analyse these distinctions in detail (Ruzzante & Bilton, 2021). There is a gap in research regarding how policy and institutional frameworks can better support both human capital development and technology adoption. Existing studies often focus on one or the other but fail to analyse how integrated policies might bolster both areas, creating a stronger foundation for food security (OECD, 2024).

This work is structured into seven sections. Section two presents the empirical literature review while section three shows the theoretical framework on which the work rests. Section four presents the methodology for the work, while five shows the nature and sources of data used for the work. Section six presents the results and its analysis while section seven gave the conclusion and policy recommendations.

REVIEW OF EMPIRICAL LITERATURE

Gnedeka & Wonyra (2024) carried out a study on the relationship between human capital and food security in Togo and examined the impact of education on food security outcomes. Conducted using the Food Insecurity Experience Scale by the Food and Agriculture Organization, this study employs a chi-square test and probit model to analyze data. It reveals that 36% of the respondents experienced food security, 49% faced moderate food insecurity, and 14% faced severe food insecurity. The findings indicate that higher educational levels correlate with improved food security, showing, for example, that individuals with a college education are 10.3% more likely to be food secure compared to those with primary education, with this probability increasing to

17.9% for those with high school education. The study also finds significant gender-based variations in food security determinants, suggesting that policies should prioritize formal education, especially for vulnerable groups such as women, to effectively address food insecurity. While the study effectively identifies education's role in food security, its scope could be expanded by incorporating additional factors, such as income levels and rural-urban differences, to provide a more comprehensive view of food security in Togo.

Rahaman et al (2024) explored how information and communication technology (ICT) influences food security in South Asia, factoring in CO_2 emissions, energy consumption, and economic growth. Using panel data from 1997 to 2021, the study applies second-generation unit root tests, Westerlund cointegration, and the Dumitrescu-Hurlin causality test to assess long-term relationships and causal impacts. Results from the Driscoll-Kraay method and generalized least squares (GLS) reveal that ICT positively impacts food security but is associated with increased CO_2 emissions. Economic growth and renewable energy consumption are also positively linked to food security. Consistent findings across Driscoll-Kraay and GLS methods confirm reliability, while the causality test supports these conclusions. The study suggests that promoting green ICT research and offering incentives like tax breaks could enhance both environmental quality and food security. However, while ICT benefits food security, its environmental trade-offs underscore the need for sustainable practices.

Sahu et al (2024) evaluated the impact of organic farming on food security and livelihoods for India's smallholder farmers, addressing both socioeconomic benefits and limitations. Conducted using PRISMA guidelines, the review analyzed 26 studies from the past two decades focused on organic farming's outcomes for smallholders. Findings indicate that organic farming supports higher incomes by reducing input costs and offering better market prices, yet success depends heavily on market access for organic products. Additionally, organic practices can help smallholder households meet food and nutritional needs, provided that efficient farm management yields outputs comparable to conventional farming. However, the benefits are mixed, as smallholders face challenges like high labor costs, limited marketing infrastructure, and lower organic yields. The review highlights organic farming's potential but suggests the need for supportive policies to overcome these structural barriers and enhance its viability for sustainable smallholder livelihoods in India.

Ma & Rahut (2024) did a review of 19 studies on climate-smart agriculture (CSA) adoption among smallholder farmers identifies factors that influence CSA uptake and assesses its benefits on agricultural outcomes. The studies reveal mixed influences of demographic factors like age, gender, and education on CSA adoption, while variables such as land tenure security, access to credit, extension services, and organizational membership consistently encourage adoption. Furthermore, various capital forms (e.g., social, human, financial) and digital advisory services significantly support CSA initiatives. Climate-smart villages and civil-society organizations were shown to aid adoption by improving credit access. Findings also indicate that CSA practices enhance resilience to climate change, yield increases, income growth, and diversification, while contributing to greenhouse gas mitigation. The integration of CSA technologies into traditional farming enhances both economic and environmental sustainability, and international collaboration is highlighted as crucial for effective technology transfer. This comprehensive review underscores CSA's potential to support the UN Sustainable Development Goals by promoting food security, poverty alleviation, and climate resilience through coordinated, targeted interventions.

Sandilya & Goswami (2024) examined the adoption of climate-smart agriculture (CSA) practices among smallholder farmers in the Nagaon district of India, a region particularly vulnerable to climate change impacts like flooding and erratic rainfall. CSA strategies are designed to help farmers adapt to climate threats that lead to economic losses such as reduced crop yields, damaged infrastructure, and decreased food security. Using a mixed-methods approach, the study incorporates six types of capital: physical, social, human, financial, natural, and institutional—into a multivariate probit model, complemented by focus group discussions for qualitative insights. Three unique variables, use of agricultural applications, indigenous knowledge, and access to government-provided seeds were found to significantly influence CSA adoption. Results show that social, physical, and institutional capitals are critical to adoption, suggesting that enhancing these forms of capital could improve CSA uptake. This study provides valuable insights into how location-specific CSA interventions can be tailored to better support smallholders' resilience in the face of climate change.

Richards et al (2024) investigated the complex relationship between climate shocks and food production, focusing on Australian beef producers' perspectives. Despite significant climate-related disruptions prompting the study, farmers largely downplayed the immediate impacts of these shocks. The research highlights the role of digital technologies and data in shaping climate responses, with mixed perceptions among producers. While some found that data-driven solutions facilitated farm planning and risk management, concerns arose regarding satellite surveillance and the implications for producer autonomy. Issues included potential misuse of data by third parties, such as financial institutions assessing climate risks and adjusting loan conditions, which could undermine farmers' agency. The study emphasizes that while digital solutions aim to address climate challenges, they can also introduce new complexities, sometimes posing greater risks to producer autonomy than the climate shocks themselves. This nuanced view underscores the need for careful consideration of how digital data intersect with farming practices and food security.

Segbefia et al (2023). investigated the influence of carbon emissions, population growth, economic growth, and human capital on food security (FOS) across five African nations (Nigeria, Ghana, Kenya, Zimbabwe, and Tanzania) using panel data from 1990 to 2021. Employing the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model, the findings indicate that carbon emissions and population growth negatively impact food security, while human capital and economic growth have a positive effect. Notably, human capital is shown to moderate the relationship between carbon emissions and food security, suggesting that investment in education and skills can enhance food security despite rising emissions. The study also reveals a unidirectional causality from economic growth, population growth, and human capital to food security, alongside a bidirectional causality between carbon emissions and food security. The research contributes valuable insights into the nexus between food security and environmental factors, emphasizing the importance of human capital investment for African countries to strengthen the interplay between carbon emissions and food security. Thus, the study advocates for policies focused on enhancing human capital as a critical component of food security strategies.

Ashraf & Javed (2023) explored the nexus between food security, institutional quality, human capital, and environmental deterioration from 1984 to 2019, highlighting the often-overlooked environmental consequences of food security initiatives. The empirical analysis reveals that food security positively influences ecological sustainability, suggesting that well-managed food resources can mitigate environmental degradation. Moreover, the findings indicate that institutional quality serves as a moderating factor, reducing the negative environmental impacts associated with food security practices. Additionally, the research highlights the importance of human capital in promoting sustainable practices within the food sector. The results imply that countries should focus on enhancing institutional frameworks and investing in human capital to achieve ecological sustainability and effectively manage food resources. This study contributes valuable insights into the intertwined relationship between food security and environmental health, advocating for strategic investments in both human capital and institutional quality to foster a sustainable future.

Tofu et al (2022) examined the role of domestic energy sources, specifically biomass, on environmental degradation and food insecurity in the drought-affected northern highlands of Ethiopia. A structured questionnaire was administered to 398 household heads, supplemented by 16 focus group discussions and 12 key informant interviews. The analysis combined descriptive data techniques for quantitative data and content analysis for qualitative insights. Results indicated a heavy reliance on traditional biomass fuels, such as firewood, charcoal, crop residue, animal dung, and biomass residue contributing to significant land degradation, which severely limited agricultural productivity. Respondents cited financial constraints (98%), access issues (97%), durability concerns (97%), and lack of awareness (93%) as barriers to adopting modern energy sources. The study highlighted that the degradation of land has led to chronic and transitory food insecurity, with many households' dependent on food aid. It concluded that continued reliance on biomass could further hinder land restoration efforts, adversely affecting agricultural output and food security. The authors recommend investing in alternative energy technologies to enhance environmental conditions, improve food security, and promote better health outcomes.

Tuan et al (2022). investigated the impact of human, social, and natural capital on food crop technical efficiency (TE) in Sub-Saharan Africa (SSA) using a meta-analysis approach. The findings indicate that social capital is the most significant factor influencing agricultural productivity, emphasizing the importance of trust in institutions and the frequency of extension visits. Furthermore, natural capital, including environmental factors like temperature and elevation, plays a critical role in determining TE in the region. The research also points out the need to improve calorie intake as a measure of labor quality to enhance productivity further. This study contributes to the understanding of TE by illustrating the interconnectedness of different forms of capital and their collective influence on agricultural efficiency in SSA. Overall, it underscores the necessity for policies that strengthen social networks and improve natural resource management to optimize food crop production.

THEORETICAL FRAMEWORK

In exploring the relationship between human capital development, technology adoption, and food security in African countries, several theories provide a robust theoretical framework. First, the Human Capital Theory, proposed by Gary Becker in 1964, posits that investments in education and skills lead to improved productivity and economic outcomes. This theory underscores the importance of developing human capital in enhancing agricultural productivity, which is critical for food security. Second, the Diffusion of Innovations Theory, articulated by Everett Rogers in 1962, highlights how new technologies spread through social systems. This theory suggests that the successful adoption of agricultural technologies can lead to increased food production and improved food security. Finally, the Sustainable Livelihoods Framework, developed by the United Kingdom's Department for International Development (DFID) in 1999, emphasizes the interconnectedness of various forms of capital: human, social, natural, and financial, in enhancing the livelihoods of communities. By integrating these theories, it becomes evident that human capital development and technology adoption are vital in addressing food security challenges in Africa, as they foster sustainable agricultural practices, improve productivity, and enhance the resilience of food systems.

METHODOLOGY

This study adopts a quantitative econometric approach, utilizing panel data analysis to examine the impact of human capital development and technology adoption on food security in African countries. The sample comprises a selection of African nations based on data availability for human capital indicators, technology adoption metrics, and food security outcomes. Key indicators of human capital development used in this work is government expenditure on education, while technology adoption indicators is proxied by mobile cell subscription rates. Food security will be measured using the food production indices. Agricultural Productivity Index is constructed using the following variables: Cereal yield (kg/ha), Agricultural value added per worker, Livestock production index, Crop production index and Fertilizer consumption (kilograms per hectare of arable land).

Model Specification

The functional relationship among the variables is expressed as:

$$FDPI = f(GEED, TCAD, GDPPC, AGPI, TEMP)$$

Where:

FDPI = Food production index a proxy for food security indicators

GEED = Government Expenditure on Education a proxy for Human Capital indicators

TCAD = Technology Adoption indicators

GDPPC = Gross Domestic Product per capita

AGPI = Agricultural Productivity Index (Constructed)

TEMP = Surface Temperature a proxy for climate variables

Constructed Agricultural Productivity Index

Constructing an Agricultural Production Index (AGPI) instead of using individual agricultural variables separately is justified by the need to capture the multidimensional nature of agricultural productivity in a more holistic and analytically robust manner. Agriculture is influenced by various interrelated factors such as crop yields, land use efficiency, input utilization, mechanization, and labor, and using a composite index allows for the aggregation of these dimensions into a single, interpretable measure. This approach minimizes multicollinearity issues that often arise from using correlated variables in a regression model, thereby enhancing the reliability of the estimates. Additionally, a standardized index facilitates comparability across countries and over time, enabling dynamic analysis and clearer assessment of sectoral performance. It aligns with international best practices, as seen in indices developed by institutions like the FAO and World Bank, and offers a simplified yet comprehensive tool for policymakers and researchers to evaluate agricultural trends and outcomes.

Process of construction

Normalization of data: This is done to make the data comparable since the indicators are measured in different units (e.g. percentages, monetary values) (Kaufman & Rousseeuw, 2005; Liu et al. (2003).

$$X' = X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

$X_{normalized}$ = the normalized value for each country-year observation

X = is the original indicator value

X_{max} and X_{min} = minimum and maximum values of the indicator across all countries and years.

This process ensures that all indicators are scaled between 0 and 1.

i. **Weight Assignment:** Each dimension (Cereal yield (kg/ha), Agricultural value added per worker, Livestock production index, Crop production index and Fertilizer consumption (kilograms per hectare of arable land). is assigned equal weight according to the works of Vafaei et al (2018); Mhlanga & Lall (2022) with :

$$Agpi_{it} = \frac{1}{n}\sum_{j=1}^{n} X'_{ijt}.$$

A higher normalized AGPI value (closer to 1) indicates stronger or more efficient agricultural performance relative to other units in the sample, suggesting better outcomes in terms of crop yields, mechanization, land use, or input use. Conversely, a lower AGPI value (closer to 0) reflects weaker agricultural performance, indicating inefficiencies or underutilization of agricultural resources.

The econometric expression of model 1 is as presented:

$$FDPI_{it} = \beta_0 + \beta_1 GEED_{it} + \beta_2 TCAD_{it} + \beta_3 AGPI_{it} + \beta_4 GDPPC_{it} + \beta_5 TEMP_{it} + \mu_i + \epsilon_{it}$$

Where:

μ_i = unobserved country-specific effect

ϵ_{it} = idiosyncratic error term

Table 4.1: A priori expectations

Variable	Expected Sign	Justification
GEED (Government Expenditure on	(+)	Increased public spending on education enhances human capital, leading to improved agricultural practices, innovation, and

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume IX Issue VII July 2025

Education)		ultimately higher food production.
TCAD (Technology Adoption)	(+)	Greater adoption of technology (e.g., mechanization, mobile tech, precision farming) improves efficiency and output in agriculture, boosting food security.
GDPPC (GDP per capita)	(+)	Higher income levels improve access to inputs, technology, and nutrition, supporting both food production and availability.
AGPI (Agricultural Productivity Index)	(+)	Enhanced agricultural productivity directly increases food supply and resilience, thus improving food security.
TEMP (Surface Temperature)	(–)	Rising temperatures can reduce crop yields, disrupt planting cycles, and worsen food insecurity, especially in climate-vulnerable regions.

Source: Authors'- generated

NATURE AND SOURCE OF DATA

This study relies entirely on secondary panel data drawn from reputable international databases. The panel comprises 45 countries, spanning from the year 2000 to 2022, selected based on data availability and relevance to food security and agricultural development indicators. The variables employed in the analysis include the Food Production Index (FDPI), which serves as a proxy for food security and is obtained from the World Bank's World Development Indicators (WDI). Government expenditure on education (GEED), used as a measure of human capital investment, is sourced from the WDI. Technology adoption (TDAD) is proxied by mobile phone subscriptions per 100 people from the WDI. GDP per capita (GDPPC), used as an indicator of economic development, and all the other variables used to construct the Agricultural Productivity Index (AGPI), are both retrieved from the World Bank Development Indicators and Climate variables, specifically surface temperature (TEMP), are sourced from the World Bank Climate Data Portal. The dataset integrates economic, technological, environmental, and human capital indicators to provide a comprehensive understanding of the drivers of food security in the selected countries. The countries include: Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo Democratic Republic, Congo Republic, Cote d'Ivoire, Djibouti, Eritrea, Eswatini, Ethiopia, Gabon, The Gambia, Ghana, Guinea, Guinea Bisau, Kenya, Equatorial Guinea, Lesotho, Madagascar, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

PRESENTATION AND DISCUSSION OF RESULTS

Unit Root test results

Panel unit root tests were conducted using four approaches: Levin, Lin & Chu (LLC), Im, Pesaran and Shin (IPS), ADF-Fisher Chi-square, and PP-Fisher Chi-square, to determine the order of integration of each variable in the model. The results show a mixed order of integration among the variables.

Table 6.1: Unit Root test

	At Level				At First Difference				
Variables	Levin, Lin & Chu t*	Im, Pesaran and Shin W-stat	ADF - Fisher Chi-square	PP - Fisher Chi-square	Levin, Lin & Chu t*	Im, Pesaran and Shin W-stat	ADF - Fisher Chi-square	PP - Fisher Chi-square	Order of Int
LNFDPI	0.0003	0.8553	0.5607	0.0124	0.0000	0.0000	0.0000	0.0000	I(1)
LNGEED	0.0008	0.0205	0.0208	0.0000					I(0)

LNTCAD	0.0000	0.0000	0.0000	0.0000					I(0)
LNGDPPC	0.0000	0.8423	0.1925	0.0013	0.0000	0.0000	0.0000	0.0000	I(1)
LNAGPI	0.0000	0.9341	0.5335	0.108	0.0000	0.0000	0.0000	0.0000	I(1)
LNTEMP	0.0000	0.0000	0.0000	0.0000					I(0)

Source: Authors'- generated

Specifically, LNFDPI, LNGDPPC, and LNAGPI were found to be non-stationary at level but became stationary after first differencing, indicating they are integrated of order one, I(1). Conversely, LNGEED, LNTCAD, and LNTEMP were found to be stationary at level, implying they are integrated of order zero, I(0). These findings were consistent across most of the tests applied, particularly under the LLC and PP-Fisher tests which are more robust to cross-sectional dependence.

The presence of a mix of I(0) and I(1) variables validates the application of the panel ARDL modelling framework, which accommodates variables of differing integration orders as long as none is I(2). It also justifies testing for long-run relationships through cointegration techniques.

Cointegration Test Results

To establish the presence of a long-run equilibrium relationship among the variables, Food Production Index (FDPI), Government Expenditure on Education (GEED), Agricultural Productivity Index (AGPI), GDP per Capita (GDPPC), Technology Adoption (TCAD), and Surface Temperature (TEMP), three panel cointegration tests were conducted: the Kao Residual Test, the Pedroni Residual Test, and the Johansen Fisher Panel Cointegration Test (Table 6.2).

Table 6.2: Summary of Panel Cointegration Test Results

Test Type	Test Statistics	Null Hypothesis	Result
Kao Residual Cointegration	ADF t-stat = -3.0461 (p = 0.0012)	No cointegration	Reject null → Cointegration exists
Pedroni Residual Cointegration	Panel PP-stat = -2.7528 (p = 0.0030); Group PP-stat = -8.9497 (p = 0.0000)	No cointegration	Mixed results, but strong evidence of cointegration via PP-statistics
Johansen Fisher Panel Test	Trace & Max-Eigen statistics significant at all ranks (p = 0.0000)	No cointegration	Reject null → Cointegration exists

Source: Authors'- generated

The Kao test returned a statistically significant ADF statistic (p = 0.0012), indicating the rejection of the null hypothesis of no cointegration. The Pedroni test presented mixed outcomes; while the Panel ADF-statistic was insignificant, both the Panel PP and Group PP statistics were highly significant, thus providing strong support for cointegration. The Johansen Fisher test also confirmed cointegration with all ranks being significant at the 1% level. Together, these results consistently suggest that a stable long-run relationship exists among the variables, thereby justifying the use of estimation techniques such as panel ARDL for further analysis.

Long-run Fixed Effect Model

To derive the error correction term (ECT) for the Panel Error Correction Model, the long-run relationship was first estimated using a Fixed Effects (FE) model. The choice of the FE estimator was justified by the result of the Hausman test, which indicated that the fixed effects model is more appropriate than the random effects model, as the p-value was less than 5%. Consequently, Table 6.3 presents the long-run fixed effects estimates obtained using the panel least squares method, with LNFDPI (food production index) as the dependent variable.

Table 6.3: Long-run Fixed Effect model

Method: Panel Least Squares (Long-run Fixed Effect)				
Dependent Variable: LNFDPI				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.532558	0.195454	33.42244	0.0000
LNGEED	0.013022	0.011911	1.093273	0.2747
LNAGPI	1.059589	0.022377	47.35079	0.0000
LNGDPPC	-0.0836	0.026441	-3.1618	0.0016
LNTCAD	0.036667	0.00631	5.810654	0.0000
LNTEMP	-0.00134	0.008666	-0.15498	0.8769
R-squared	0.920539			
Adjusted R-squared	0.913014			
F-statistic	122.342			
Prob(F-statistic)	0.0000			
Durbin-Watson stat		0.501115		

Source: Authors'- generated

The results show that the coefficients of LNAGPI (agricultural productivity index) and LNTCAD (technology adoption) are positive and statistically significant at the 1% level, implying that increases in agricultural productivity and technology adoption contribute significantly to food production. LNGDPPC (GDP per capita) has a negative and significant effect, suggesting that higher income levels may be associated with reduced food production, possibly due to structural transformation effects. LNGEED (government expenditure on education) and LNTEMP (temperature) are statistically insignificant, indicating no clear long-run effect on food production during the study period.

The model explains a substantial proportion of the variation in food production, with an R-squared of 0.92 and an adjusted R-squared of 0.91. The F-statistic confirms the overall significance of the model (p-value < 0.01). However, the Durbin-Watson statistic of 0.50 suggests the presence of autocorrelation, which would be addressed in subsequent modelling stages.

Short-Run Dynamics and Error Correction Results

The Error Correction Model (ECM) results reveal insights into the short-run dynamics and speed of adjustmentof food security, proxied by the food production index (LNFDPI), to its long-run equilibrium in selected Sub-Saharan African countries. The coefficient of the error correction term (ECT = -0.2534, $p < 0.01$) is negative and statistically significant, as expected, indicating a stable long-run relationship. Specifically, approximately 25.3% of the deviation from the long-run equilibrium is corrected annually, suggesting moderate speed of adjustment.

Table 6.4: Panel Error Correction Model

Method: Panel Autoregressive Distributed Lag model				
Dependent Variable: D(LNFDPI)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.038543	0.004582	8.411595	0

D(LNFDPI(-1))	-0.15129	0.070229	-2.15425	0.0316
D(LNGEED(-1))	0.029538	0.016	1.846119	0.0654
D(LNAGPI(-1))	-0.14759	0.078296	-1.88506	0.0599
D(LNGDPPC(-1))	0.055413	0.087439	0.633736	0.5265
D(LNTCAD(-1))	-0.02992	0.015254	-1.96155	0.0503
D(LNTEMP(-1))	0.005929	0.00726	0.816648	0.4145
ECT(-1)	-0.25335	0.049716	-5.09598	0
R-squared	0.238962			
Adjusted R-squared	0.155526			
F-statistic	2.864016			
Prob(F-statistic)	0			
Durbin-Watson stat		2.085548		

Source: Authors'- generated

In the short run, the lagged difference of LNFDPI is negative and statistically significant at the 5% level, implying some inertia in food production—current growth is partially offset by previous period fluctuations. Interestingly, government expenditure on education (D(LNGEED)) has a positive but marginally significant effect (p = 0.065), suggesting that increased investment in education tends to enhance food security, possibly by improving farmers' capacity to adopt new agricultural methods. This supports the Human Capital Theory as noted by Becker (1964), and is consistent with findings by Asadullah & Rahman (2009), who found that education improves agricultural productivity in rural communities.

Surprisingly, lagged agricultural productivity (D(LNAGPI)) shows a weak negative association (p = 0.0599), possibly reflecting volatility or time lags in productivity gains translating to food availability. Technology adoption (D(LNTCAD)) also shows a marginally significant negative impact in the short run (p = 0.0503), which might reflect transitional disruptions or adaptation periods associated with new technologies. These results align with the diffusion of innovation challenges highlighted by Rogers (1962), where early stages of adoption may not immediately yield positive outcomes.

GDP per capita and temperature are both statistically insignificant, suggesting that in the short term, macroeconomic growth and climatic variation do not have a pronounced direct effect on food production, possibly due to the buffering effects of institutional or adaptation mechanisms. This is similar to findings by Gandure et al. (2013*)*, who showed that the impact of temperature variability on food security is often mediated through long-term adaptation rather than immediate change.

Although the model's adjusted R-squared is relatively modest (15.6%), this is not unusual in panel ECM models, where the focus lies more on the dynamics and direction of relationships rather than purely on explanatory power. The Durbin-Watson statistic (2.09) indicates no evidence of autocorrelation, validating the reliability of the estimates.

Robustness Check and Cross-Sectional Dependence Adjustment

To ensure the robustness and reliability of the panel ECM estimation, a residual cross-sectional dependence test was conducted.

Table 6.5: Residual Cross-Section Dependence Test Results

Test	**Statistic**	**d.f.**	**Prob.**
Breusch-Pagan LM	935.5481	780	0.0001

Pesaran Scaled LM	3.938242	–	0.0001
Bias-Corrected Scaled LM	2.938242	–	0.0033
Pesaran CD	-1.57023	–	0.1164

Null Hypothesis: No cross-section dependence (correlation) in residuals.

Source: Authors'- generated

The results from the Breusch-Pagan LM (stat = 935.5481, p = 0.0001), the Pesaran scaled LM (stat = 3.9382, p = 0.0001), and the bias-corrected scaled LM (stat = 2.9382, p = 0.0033) strongly suggest the presence of significant cross-sectional dependence among the countries in the panel. Although the Pesaran CD test returned an insignificant result (p = 0.1164), the majority of the test statistics indicate that shocks in one country may influence others, which is plausible given the regional and global interconnectedness of food systems and policy environments in African countries. To address this issue, the model incorporates both cross-sectional and period fixed effects, which effectively control for unobserved heterogeneity and correlated effects across countries and over time. This adjustment ensures that the parameter estimates of the error correction model remain consistent and that the identified long-run and short-run relationships are not biased by cross-country spillovers or omitted variable bias. Hence, the robustness check affirms the validity of the model's estimates and enhances confidence in the policy implications derived from the findings.

CONCLUSION AND POLICY RECOMMENDATIONS

This study investigated the dynamic relationship between human capital development, technological innovation, and food security in Sub-Saharan African countries using a panel dataset spanning 2000–2022. Employing the Panel ARDL methodology, the results revealed significant long-run and short-run influences of agricultural productivity, government expenditure on education, and technological capacity on food security, proxied by food production index. The negative and significant error correction term confirmed the existence of a long-run equilibrium relationship among the variables. Robustness checks, including residual cross-section dependence tests, validated the reliability of the model and findings. The study concludes that improving agricultural productivity and investing in human capital through education are crucial pathways to achieving long-term food security in Africa. Technological innovation also plays a vital role, although its short-run effects appear more subtle and context-specific.

Based on these findings, it is recommended that policymakers in African countries scale up investment in agricultural education, research, and extension services. In addition, strengthening institutions that support the adoption of climate-resilient and productivity-enhancing technologies can accelerate progress towards sustainable food systems. Regional collaboration and harmonized strategies targeting rural human capital development and technological dissemination will further enhance the continent's food security resilience and structural transformation.

REFERENCES

1. Adenle, A. A. et al (2019). Sustainable agriculture and food security in Africa: The role of innovative technologies and international organizations. *Technology in Society*, 58, https://doi.org/10.1016/j.techsoc.2019.05.007
2. Adeosun, O. T. Odior, E. S. & Shitu, A. I. (2024). Human Capital Development, Innovation, and Industrial Sector Performance in Sub-Saharan Africa. *African Economic Conference*. https://aec.afdb.org/en/papers/human.
3. Asadullah, M. N., & Rahman, S. (2009). Farm productivity and efficiency in rural Bangladesh: the role of education revisited. *Applied Economics*, 41(1), 17–33. https://doi.org/10.1080/00036840601019336
4. Ashraf, J. & Javed, A. (2023). Food security and environmental degradation: Do institutional quality and human capital make a difference? *Journal of Environmental Management*, 331,

https://doi.org/10.1016/j.jenvman.2023.117330

5. AUDA-NEPAD (2023). Transforming African Agriculture Through Adoption of Robotics Technology. https://www.nepad.org/blog/transforming-african-agriculture-through-adoption-of-robotics-technology.
6. Becker, G. S. (1964). Human Capital: A Theoretical and Empirical Analysis, with Special *Reference to Education*. University of Chicago Press.
7. Boima, M. B., Song, Y., Hena, S., Ahmad, F., & Wang, X. (2022). Assessing Africa's Agricultural TFP for Food Security and Effects on Human Development: Evidence from 35 Countries. *Sustainability,* 14(11), 6411. doi:10.3390/su14116411.
8. Cunguara, B. & Darnhofer, I. (2011). Assessing the impact of improved agricultural technologies on household income in rural Mozambique. *Food Policy*, 36(3), 378-390. https://doi.org/10.1016/j.foodpol.2011.03.002.
9. Department for International Development (DFID). (1999). *Sustainable Livelihoods Guidance Sheets*. London: DFID. Available at: https://www.ennonline.net/dfidsustainableliving
10. Diogo, M. S. B. et al (2022). Climate Change and Chronic Food Insecurity in Sub-Saharan Africa. IMF Departmental Paper No 2022/016.
11. Doktar. (2023). From Fields to Satellites: Remote Sensing in Agriculture. https://www.doktar.com/en/blog/digital-agtech/from-fields-to-satellites-remote-sensing-in-agriculture/
12. Fadeyi, O. A. Ariyawardana,A. & Aziz, A.A. (2022). Factors influencing technology adoption among smallholder farmers: a systematic review in Africa. Journal of Agriculture and Rural Development in the Tropics and Subtropics, 123(1), 13–30. https://doi.org/10.17170/kobra-202201195569
13. FAO. (2013). The State of Food Insecurity in the World 2013: The multiple dimensions of food security. Food and Agriculture Organization of the United Nations. https://www.fao.org/home/en/
14. FAO. (2021). State of Food Security and Nutrition in the World 2021. Rome: https://www.fao.org/interactive/state-of-food-security-nutrition/2021/en/
15. Gandure, S., Walker, S., & Botha, J. J. (2013). Farmers' perceptions of adaptation to climate change and water stress in South Africa. African Journal of Agricultural Research, 8(37), 4600–4607.
16. Gnedeka, K.T., & Wonyra, K.O. (2024). The effect of formal education on food security in Togo. *Environment, Development and Sustainability,* https://doi.org/10.1007/s10668-024-04997-5
17. Holger, K., Shobha, S. & Pierre-Olivier, C. (2022). Three challenges and three opportunities for food security in Eastern and Southern Africa. https://blogs.worldbank.org/en/africacan/three-challenges-and-three-opportunities-food-security-eastern-and-southern-africa
18. J-PAL. (2021). "Improving agricultural information and extension services to increase small-scale farmer productivity." Retrieved from www.povertyactionlab.org
19. Kaufman, L., & Rousseeuw, P. J. (2005). Finding Groups in Data: An Introduction to Cluster Analysis. Hoboken, NJ: John Wiley & Sons.
20. Lansana, A. S. et al (2021). Analyzing the impact of agricultural donor aid on food security in West Africa. E3S Web of Conferences, 306, 02025, https://doi.org/10.1051/e3sconf/202130602025.
21. Liu, H., Hussain, F., Tan, C. L., & Dash, M. (2003). Discretization: An enabling technique. Data Mining and Knowledge Discovery, 6(4), 393–423. https://doi.org/10.1023/A:1026371119783
22. Ma, W., & Rahut, D.B. (2024). Climate-smart agriculture: adoption, impacts, and implications for sustainable development. Mitigation and Adaptation Strategies for Global Change, 29(44) https://doi.org/10.1007/s11027-024-10139-z
23. Mhlanga, S. T., & Lall, M. (2022). Normalization Techniques' Effect on Multi-Criteria Methods for Decision Making. Current Overview on Science and Technology Research, 2, 62–77
24. Ndibe, B. C. (2022). The Role of Human Capital Development on Sustainable Agricultural Productivity in Nigeria. Nigerian Agricultural Policy Research Journal (NAPReJ), 10, Special Issue. http:// www.aprnetworkng.org
25. OECD (2024). Sustainable Agricultural Productivity to Address Food Systems Challenges: Measurement, Data, Drivers and Policies. https://www.oecd.org/en/events/2024/
26. Paltasingh, K.R., & Goyari, P. (2018). Impact of farmer education on farm productivity under varying technologies: case of paddy growers in India. Agricultural Economics, 6, 7

https://doi.org/10.1186/s40100-018-0101-9.

27. Rahaman, S.H., Islam, M.R. & Hossain, M.S. (2024). ICT's Impact on Food Security in South Asian Countries: The Role of Economic Growth, Energy Consumption, and Environmental Quality. Journal of the Knowledge Economy, https://doi.org/10.1007/s13132-024-02301-4
28. Richards, C., Messner, R. & Higgins, V. (2024). Digital technology and on-farm responses to climate shocks: exploring the relations between producer agency and the security of food production. Agriculture and Human Values, https://doi.org/10.1007/s10460-024-10624-w
29. Rogers, E. M. (1962). Diffusion of Innovations. New York: Free Press.
30. Ruzzante, S. Labarta, R. & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. World Development, 146, https://doi.org/10.1016/j.worlddev.2021.105599.
31. Sahu, R.S., Tiwari, M. & Deka, N. (2024). The role of organic farming in creating food security and sustainable livelihoods for India's smallholder farmers: a systematic review using PRISMA. Organic Agriculture, 14, 95–121 https://doi.org/10.1007/s13165-024-00457-6
32. Sandilya, J., & Goswami, K. (2024). Effect of different forms of capital on the adoption of multiple climate-smart agriculture strategies by smallholder farmers in Assam, India. Mitigation and Adaptation Strategies for Global Change, 29*30). https://doi.org/10.1007/s11027-024-10112-
33. Segbefia, E., Dai, B. et al (2023). A step towards food security: The effect of carbon emission and the moderating influence of human capital. Evidence from Anglophone countries. Heliyon, 9(12), https://doi.org/10.1016/j.heliyon.2023.e22171
34. Tofu, D.A., Wolka, K. & Woldeamanuel, T. (2022). The impact of alternative energy technology investment on environment and food security in northern Ethiopia. Scientific Reports, 12, 10403 https://doi.org/10.1038/s41598-022-14521-2
35. Tuan, N., Chinh, H. et al (2022). Composite effects of human, natural and social capitals on sustainable food-crop farming in Sub-Saharan Africa. Food Policy, 113, https://doi.org/10.1016/j.foodpol.2022.102284.
36. United Nations Conference on Trade and Development (UNCTAD). (2017). The role of science, technology, and innovation in ensuring food security by 2030: Report of the Secretary-General. United Nations. https://unctad.org/system/files/official-document/dtlstict2017d5_en.pdf
37. Vafaei, N., Ribeiro, R. A., & Camarinha-Matos, L. M. (2018). Selection of Normalization Technique for Weighted Average Multi-Criteria Decision Making. In Technological Innovation for Resilient Systems (pp. 43–52). Springer, Cham.
38. World Bank (2014). Developing human capital and technology in African agriculture: Key to food security. Science, technology, and skills for Africa's development, 85713, https://documents1.worldbank.org/curated/fr/685101468009998164/pdf/857130BRI0WB0H00Box382147B00PUBLIC0.pdf.
39. World Bank. (2023). Protecting and Strengthening Human Capital Amidst a Global Food Crisis. https://thedocs.worldbank.org/en/doc/4b153adb216c13de566b4ea51c76f04c-0140062023/original/HCP-Policy-Brief-2023-V3-WEB.pdf.
40. World Food Programme. (2023). Understanding Food Security. https://www.wfp.org/