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Exploring the Contributions of Human Capital Development to Food Security in African Countries: The Mediating Influence of Technology Adoption

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Abstract: Achieving food security constitutes one of the utmost pressing developmental challenges in Africa, where millions continue to face hunger, malnutrition, and unstable food supplies despite the continent's vast agricultural potential. The synergy between human development and technology adoption can significantly enhance agrarian output, improve food distribution systems, and build resilience against climate shocks. This study examines the impact of human capital development and technology adoption on food security in African countries. The study utilises data from the ND-GAINS Index and the WDI for 43 developing African economies, encompassing 44 annual observations and spanning the period from 2012 to 2023. The Generalised Method of Moments (GMM) and the Panel Quantile Regression (PQR)approaches were adopted for analysing the data. The study findings showed that human capital development has a negative and significant effect on food security. Also, the adoption of technology has a negative and significant impact on food security. Moreover, the interactive effect of human capital development and technology adoption is statistically significant and negative in relation to food security. Accordingly, the study recommends that governments in African countries should improve investment in education and skills acquisition to support the implementation of new technology in agricultural productivity. Additionally, African governments should provide farmers with credit facilities and enhance the level of infrastructure, such as internal roads, to help local farmers increase their earnings from agricultural sales.

Keyword: *Food Security, Human Capital Development, Technology Adoption, Generalised Method of Moments, Quantile Regression.*

JEL Codes: *J24; Q16; I25; O15.*

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I. INTRODUCTION

Food security has remained a critical yet intricate issue for African countries. Over the past few decades, food demand in Africa has consistently outpaced supply, resulting in persistent food insecurity across the continent. The empirical study by the Food and Agriculture Organisation (FAO) shows 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 multidimensional concept that encompasses consistent and equitable access to nutritious and

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safe food, necessary for a healthy life. The Food and Agriculture Organisation (FAO) maintain that food security becomes apparent 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 proportions: access, utilisation, availability 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, encompasses both the physical and economic factors that enable people to obtain food, emphasising income levels, market infrastructure, and affordability as key determinants of whether individuals can access and afford food (FAO, 2013). Utilisation addresses food safety, nutrition, and the knowledge required for proper dietary intake, recognising 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 recognising 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 recognised as essential drivers of food security and agricultural resilience (Alenoghena et al., 2025). Human capital, entailing the health, education, skills, and overall productivity of a workforce, is a fundamental asset for achieving agricultural growth. In agricultural contexts, human capital has a direct influence on farmers' ability to innovate, adapt to new practices, and utilise resources efficiently (Ndibe, 2022). Studies 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 optimise 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 mechanisation reduces labour intensity and improves efficiency in crop harvesting and soil preparation (Adenle et al, 2019; Cunguara & Darnhofer, 2011).

Human capital development is fundamental to fostering food security. The World Bank (2023) describes it as the accumulation of skills, knowledge, and health that individuals possess, which directly contributes to productivity. In agriculture, human capital is essential for the adoption of sustainable agricultural practices, efficient use of inputs, and adaptation to changing environmental conditions. Studies have shown that farmers possessing higher levels of education and training are more likely to espouse modern agricultural technologies, engage in environmentally sustainable practices, and increase yields (Fadeyi et al., 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).

Despite the promising outlook for human capital and technology adoption in improving food security, many African countries face significant gaps in education and access to technology. Rural areas, where the majority of agricultural activities take place, are often under-resourced, limiting farmers' opportunities 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 et al., 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 a significant share of the global agricultural workforce, Africa has considerable potential to become a major player in the global food system. 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. The synergy between human capital development and technology adoption has a substantial impact on food security. A skilled and formally trained workforce is more likely to effectively leverage technological advancements, thereby maximising productivity and minimising environmental impacts. As African governments and development organisations work to improve food security, understanding how these two elements—human capital and technology—interact and contribute to agricultural outcomes is crucial (David Adebisi et al., 2025). Despite substantial evidence on their importance, a knowledge gap remains concerning the combined effect of human capital and technology on food security outcomes. This study aims to fill that gap by investigating the role of human capital development and technology adoption in fostering the food security status of African countries and assessing the barriers and opportunities associated with these interventions.

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Understanding this relationship has broad implications for policymakers, development practitioners, and agricultural stakeholders. It could inform future investments and initiatives aimed at promoting 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 essential insights for designing effective policies and programs that address the fundamental problems of food insecurity in Africa. Although substantial investments in agricultural development have been made, food insecurity firmly remains a considerable challenge in Africa. Many African countries face structural issues, including 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 restricted 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 policymakers' ability to make data-driven decisions about where to allocate resources most effectively. Additionally, studies have shown varying impacts of technology on productivity in the absence of adequate human capital, highlighting the need for policies that jointly address educational needs and technological support in agriculture (Boima et al., 2022; Lansana et al., 2021).

While extensive research has been conducted on the benefits of human capital and technology in agriculture globally, there is a notable shortage of studies specifically focused on Africa. Most studies generalise findings from Asia and Latin America, which may not account for Africa's unique socioeconomic and climatic conditions (Fadeyi et al., 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 mechanised equipment, but few studies analyse these distinctions in detail (Ruzzante et al., 2021). There is a gap in research regarding how policy and institutional frameworks can better support both human capital development and the adoption of technology. 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).

II. REVIEW OF EMPIRICAL LITERATURE

Gnedeka & Wonyra (2024) conducted a study on the effect of human capital on food security in Togo. The authors examined the impact of education on food security outcomes. Employing a chi-square test and a probit model, the authors investigated the Food Insecurity Experience Scale in accordance with the Food and Agriculture Organisation's procedure. The results reveal that 36% of the total respondents experienced food security. Moreover, 49% faced moderate food insecurity, while 14% faced severe food insecurity. The findings indicate that higher educational levels are correlated with improved food security. More specifically, individuals with a college education are 10.3% more likely to be food secured when compared to those with primary education, with this probability increasing to 17.9% for those with a high school education. The study also reveals significant gender-based variations in food security determinants, indicating that policies should prioritise formal education, particularly for vulnerable groups such as women, to address food insecurity effectively. While the study effectively identifies the role of education 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 the relationship between information and communication technology and food security in South Asia, taking into account energy consumption, CO_2 emissions, and economic growth in the country. The study employed second-generation unit root tests, Westerlund cointegration, and the Dumitrescu-Hurlin causality test to examine long-term relationships and causal impacts on panel data spanning the period from 1997 to 2021. Results from the Driscoll-Kraay method and generalised least squares (GLS) indicate that ICT has a positive effect on food security but is associated with increased CO_2 emissions. Renewable energy consumption and economic growth are positively associated with 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, such as tax breaks, could enhance both environmental quality and food security. However, while ICT benefits food security, its ecological 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 in accordance with PRISMA guidelines, the review analysed 26 studies from the past two decades that focused on the outcomes of organic farming 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 their food and nutritional needs, provided that efficient farm management yields outputs comparable to those of conventional farming. However, the benefits are mixed, as smallholders face challenges such as high labour costs, limited marketing infrastructure, and lower organic yields. The review highlights the potential of organic farming 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) conducted a review of 19 studies on climate-smart agriculture (CSA) adoption among smallholder farmers, identifying factors that influence CSA uptake and assessing its benefits on agricultural outcomes. The studies reveal mixed influences of demographic characteristics, such as age, gender, and education, on the adoption of CSA. At the same time, variables like land tenure security, access to credit,

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extension services, and organisational membership consistently encourage adoption. Furthermore, various forms of capital (e.g., social, human, and financial) and digital advisory services provide significant support to CSA initiatives. Climate-smart villages and civil society organisations were found to aid adoption by improving access to credit. 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 highlights the potential of CSA to support the UN Sustainable Development Goals by promoting food security, alleviating poverty, and enhancing climate resilience through coordinated and 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, such as 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 —the use of agricultural applications, indigenous knowledge, and access to government-provided seeds — were found to influence CSA adoption significantly. 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) examined the intricate relationship between climate shocks and food production, with a focus on the perspectives of Australian beef producers. Despite the significant climate-related disruptions that prompted 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 the potential misuse of data by third parties, such as financial institutions assessing climate risks and adjusting loan conditions, which could undermine farmers' autonomy and agency. The study emphasises 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 highlights the importance of carefully considering how digital data intersects with farming practices and food security.

Segbefia et al. (2023) investigated the effects of economic growth, human capital, carbon emissions, and population growth on the food security status of five African countries, including Kenya, Tanzania, Nigeria, Zimbabwe, and Ghana. The study employed the cross-sectional augmented autoregressive distributed-lag (CS-ARDL) model on panel data spanning the period from 1990 to 2021. The findings showed that the effect of carbon emissions and population growth on food security is negative and significant. Conversely, the effect of human capital and economic growth was positive on food security. 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 that a unidirectional causality exists between population, human capital, and economic growth, and food security. Additionally, a bidirectional relationship exists between carbon emissions and food security. The research offers valuable insights into the nexus between food security and environmental factors, emphasising the importance of human capital investment for African countries to optimise the interplay between carbon emissions and food security. Thus, the study advocates for policies focused on improving human capital as a vital component of measures to enhance food security on the continent.

Ashraf & Javed (2023) explored the nexus between food security, institutional quality, human capital, and environmental deterioration from 1984 to 2019, highlighting the often-overlooked ecological consequences of food security initiatives. The empirical analysis reveals that food security has a positive influence on ecological sustainability, suggesting that well-managed food resources can help mitigate environmental degradation. Moreover, the findings suggest that institutional quality acts as a moderating factor, mitigating the negative environmental impacts associated with food security practices. Furthermore, the research highlights the importance of human capital in promoting sustainable practices within the food sector. The results suggest that countries should prioritise enhancing their institutional frameworks and investing in human capital to achieve ecological sustainability and effectively manage food resources. This study offers valuable insights into the intricate 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) investigated the impact of domestic energy sources, particularly biomass, in Ethiopia, and how it affects food security and environmental degradation, with a focus on the drought-affected parts of the northern highlands. The survey conducted involved administering a structured questionnaire to 398 household heads. Twelve key informants were interviewed, and their findings were supplemented with 16 focus group discussions. The study's mode of analysis was a combination of descriptive data techniques and content analysis, resulting in a mix of qualitative and quantitative data insights. The study findings revealed a significant dependence on traditional biomass fuels, such as animal dung, biomass waste, firewood, and crop residue, as

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substantial contributors to land degradation that severely inhibited 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 land degradation has led to chronic and intermittent food insecurity, with many households dependent on food aid. It concluded that continued reliance on biomass could further hinder land restoration efforts, negatively impacting farm productivity and food security. The authors recommend government investment in alternative energy sources to improve environmental conditions, enhance food security standards, 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, emphasising the importance of trust in institutions and the frequency of extension visits. Furthermore, natural capital, including environmental factors such as temperature and elevation, plays a crucial role in determining TE in the region. The research also highlights the need to improve calorie intake as a measure of labour quality to further enhance productivity. 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 highlights the need for policies that strengthen social networks and enhance natural resource management to optimise food crop production.

III. THEORETICAL FRAMEWORK

In exploring the relationship between human capital development, technology adoption, and food security in African countries, several theories serve as benchmarks to provide a robust theoretical framework for a better understanding of this complex relationship. First, the Human Capital Theory, proposed by Gary Becker in 1964, posits that investments in skills training and education lead to enhanced productivity and favourable economic outcomes. This theory underscores the relevance of developing human capital to enhance agricultural productivity, a crucial factor in ensuring 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 champion an increase in food production and enhance food security. As a follow-up, the Sustainable Livelihoods Framework, advanced by the United Kingdom's Department for International Development (DFID) in 1999, focuses on the interconnectedness of various forms of capital, including human, financial, natural, and social capital, in enhancing the livelihoods of communities. By integrating these theories, it becomes evident that human capital development and technology adoption are crucial in devising policy solutions to Africa's food security challenges. Government policy in this direction will focus on promoting sustainable agricultural practices, improving the resilience of food systems, and enhancing agricultural productivity (Alenoghena et al., 2023).

IV. METHODOLOGY AND MODEL SPECIFICATION

This study employs a quantitative econometric strategy, utilising panel data analysis, to explore the impact of human capital development and technology adoption on the food security status of 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 will include secondary school enrollment rates, literacy rates, and public expenditure on education. Technology adoption indicators will encompass agricultural technology uptake rates, mobile penetration rates, and internet access levels. Food security will be measured using the prevalence of undernourishment, food production indices, and other relevant metrics.

➢ *Model Specification*

The model adopted in this study follows the study by Ashraf & Javed (2023). The model expresses the Food Security Index (FSI) as the dependent variable and the Human Development Index (HDI) and Technology Adoption (TECH) as independent variables. The control variables in the model include Agricultural Output (AGRIC), Population Growth Rate (POPN), Inflation (INFL), Gross Fixed Capital Formation (GFCF) and Government Effectiveness (GEFF) as the explanatory variables.

- *The Variables are Presented in Equation (1) as Follows:*

FSI = (HDI, TECH, AGRIC, POPN, INFL, GFCF, GEFF)- - - - -(1)

Equation (1) can be further expressed in a functional form as shown in equation (2)

$$FSI_t = \beta_0 \cdot (HDI_{it})^{\beta_1} \cdot (TECH_{2t})^{\beta_2} \cdot (AGRIC_{3t})^{\beta_3} \cdot (POPN_{4t})^{\beta_4} \cdot (INFL_{5t})^{\beta_5} \cdot (GFCF_{6t})^{\beta_6} \cdot (GEFF_{7t})^{\beta_7} \quad - \quad - \quad (2)$$

The next step is to log-linearise Equation (3) for ease of estimation. The process of log-linearization is necessary to effectively streamline the variable scales reduce the data fluctuations. Hence:

$$LnFSI_t = \beta_0 + \beta_1 LnHDI_{t1} + \beta_2 LnTECH_{t2} + \beta_3 LnAGRIC_{t3} + \beta_4 LnPOPN_{t4} + \beta_5 LnINFL_{t5} + \beta_6 LnGFCF_{t6} + \beta_7 LnGEFF_{t7} + \mu_t \text{ - - - - - - - - - - - -(3)}$$

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Equation (3) can be used to empirically investigate the impact of human development on food security. The same equation (3) will be adopted to study the effect of technology adoption on food security. Another equation is designed to assess the synergistic impact of human capital development and technology adoption on the food security index of African countries.

$$LnFSI_t = \beta_0 + \beta_1 LnHDI_{t1} + \beta_2 LnTECH_{t2} + \beta_3 LnHDI * LnTECH_{t3} + \beta_4 LnAGRIC_{t4} + \beta_5 LnPOPN_{t5} + \beta_6 LnINFL_{t6} + \beta_7 LnGFCF_{t7} + \beta_8 LnGEFF_{t8} + \mu_t \text{- - - - - - -(4)}$$

Where $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5,\ \beta_6$ & β_7 are the coefficient values to be calculated in Equations 3 and 4. μ_t is the stochastic error term that is associated with the models.

Furthermore, the apriori expected signs of the model for equations (3 and 4): $\beta_1 > 0$; $\beta_2 > 0$; $\beta_3 > 0$; $\beta_4 > 0$; $\beta_5 > 0$; $\beta_6 > 0$ & $\beta_7 > 0$.

➢ *Sources of Data and Variable Description*

The data for this study was obtained from Notre Dame Global Adaptation Index and World Development Index (World Bank) statistics. The description and measurement of all the variables is shown in Table 1.

Table 1 Description and Measurement of Variables

Variable	Description and Measurement	Source
FSI	Food security refers to a situation where all people, at any given point in time, have physical, economic, and social access to healthy, adequate, and safe food. The index that is constructed to take account of availability, accessibility, adequacy, acceptability and agency of food supply.	ND-GAIN
HDI	The Human Capital Development Index measures the contributions of skills and training, formal education, and wellbeing to a worker's productivity. The score of the index ranges between zero and one, indicating the productivity capacity of an ideal worker who is in full health and has a good educational standard.	ND-GAIN
TECH	High-technology import. These are the products of high R&D content, such as in electrical engineering, telecoms, automobiles, aerospace, pharmaceuticals, computer science and buildings.	WDI
AGRIC	Agricultural sector output refers to the total value or quantity of goods and services produced within the agricultural industry during a specific period. This covers activities including crop production, livestock farming, forestry, fishing, and related support services. It is a ratio of GDP.	WDI
POPN	Population: Refers to growth in total population based on the concept of population definition involving the count of all residents. The count is regardless of legal standing or citizenship. The values recorded are mid-year approximations.	WDI
INFL	The inflation rate is based on the consumer price index. The estimate specifies the yearly change depending on the prices of the average consumer items. The terms included comprises of a selected basket of goods and services annually. The Laspeyres formula is used	WDI
GFCF	The estimate comprises land improvements (like drains, fences, ditches), schools' development, commercial buildings, plant and machinery, road construction, hospitals, industrial buildings and equipment purchases.	WDI
GEFF	The Government Effectiveness Index estimates the quality of public services provided by governments, the quality of public policy formulation, the level of independence from political pressures, the quality of the country's public service, the efficiency of government policy implementation, and the credibility of the government's commitment to public policies.	WDI

Source: Collated from WDI and ND-GAIN (2023)

- *Selected Countries*

The data for this research study comprises annual time series of panel data spanning 44 years (2012-2023) for 43 developing African countries. Algeria, Angola, Benin, Central African Republic, Burkina Faso, Burundi, Cameroon, Congo Republic, Djibouti, Botswana, Chad, Congo Dem Rep. Cote d'Iviore, Egypt, Madagascar, Mali, Ethiopia, Gambia, Guinea, Equitorial Guinea, Garbon, Ghana, Guinea Bisau, Kenya, Sierra Leone, South Africa, Mauritania, Morocco, Lesotho, Libya, Mauritius, Namibia, Nigeria, Senegal, Sudan, Niger, Rwanda, Tanzania, Tunisia, Zimbabwe, Togo, Uganda and Zambia.

➢ *Estimation Strategy*

The estimation procedure for this research study entails a five-step procedure. First, the dataset for the study is analysed utilising descriptive statistics and the correlation matrix of regressors. Second, an analysis of the econometric

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stability of the conducted using the ADF, Fisher's Chi-Square, and the Levin, Lin, and Chu unitary root tests. The third step is the Cointegration test using the Pedroni residual approach. The fourth step involves panel regression using the Generalised Method of Moments (GMM), and the fifth step entails an analysis using the Quantile regression approach. The relationship evaluation for the variables covers the period from 2012 to 2023. The generalised method of moments approach (GMM) is the analytical framework adopted for this study. The GMM model employs an instrumental variable approach and hence holds superiority over the conventional two-stage least squares (2SLS) model. The methodology suggests the one-step GMM model, which is a suitable choice for the regression analysis of panel data in this study and can be considered unbiased. The framework was developed by Arellano and Bond (1991) for analysing the application of various approaches to GMMs, including OLS and WG as estimators.

Researchers have observed that GMM estimators show slight bias and variation through simulations. Hence, Hayashi (2011) argues that GMM models employ an orthogonality approach, which ensures the achievement of unbiased results in the presence of heteroscedasticity in the data. Thus, this study employs the version of the panel regression that employs Arellano and Bond's (1991) GMM estimators. Thus, the proposed model for this study, which employs the Arellano and Bond GMM estimator, is shown as follows in (6).

$$FSI_{\text{it}} = \beta_0 HDI_{\text{it}-1} + \beta_1 TECH_{\text{it}} + \beta_2 AGRIC_{\text{it}} + \beta_3 POPN_{\text{it}} + \beta_4 INFL_{\text{it}} + \beta_5 GFCF_{\text{it}} + \beta_6 GEFF_{\text{it}} + \sum_{j=1}^{5} \theta_j Z_{it} + \mu_{it} + \varepsilon_{it} - \quad (6)$$

In equation (6), β_0 is only estimated when the core independent variables vector is controlled. Also, the country-specific effects is specified in μ_{it}, while ε_{it} symbolizes the stochastic error term. Accordingly, the coefficients $\beta_1$to β_6 will be estimated using the random effects of HDI, TECH, AGRIC, POPN, INFL, GFCF and GEFF respectively. The model is configured in consonance with the GMM estimators proposed by Arellano and Bond (1991). The keynote of the GMM model is ability to handle endogeneity, measurement errors, and heteroscedasticity in data.

The second analytical framework adopted in this research study involves the adoption of the panel quantile regression (PQR) estimation method, which is engaged to reinforce the results of the GMM estimates and provide a robustness check on the regression estimates concerning the random effects values on the specified independent variables: HDI, TECH, AGRIC, POPN, INFL, GFCF and GEFF, respectively. Therefore, the PQR model is specified as follows in equation 7.

$$Q_{FSI_{\text{it}}}(\tau_k|\beta_i X_{it}) = +\beta_1 HDI_{\text{it}} + \beta_2 TECH_{\text{it}} + \beta_3 AGRIC_{\text{it}} + \beta_4 POPN_{\text{it}} + + \beta_5 INFL_{\text{it}} + \beta_4 GFCF_{\text{it}+} + \beta_4 GEFF_{\text{it}} + \varepsilon_{it} - \quad (7)$$

The Quantile Regression equation signifies that “t” denotes the time period from 2012 to 2023 and “i” represents the sampled countries. Also, "τ" indicates the quantiles conditional contributions and β_i epitomises the unobserved specific effects. To explanatory variables (HDI, TECH, AGRIC, POPN, INFL, GFCF, GEFF) are positioned to investigate the effect of the coefficients on the dependent variable FSI. Hence, the analysis generating the coefficients ensures the resolution of the conditional distribution of the τth quantile.

$$\widehat{\beta(\tau)} = argmin \sum_{i=1}^{n} \rho_\tau(y_i) = x_i^\tau \beta \quad - \quad - \quad - \quad (5)$$

On a general note, the panel quantile regression (PQR) approach offers several benefits over traditional analysis methods, such as OLS, in analysing panel data. Primarily, the PQR permits an examination of the associations between variables with variations across different parts of a conditional distribution involving the dependent variable. Hence, the PQR provides a richer, nuanced understanding beyond the mean. The PQR is particularly beneficial when handling situations with non-normal distributions or when investigating how the effects differ in relation to the high and low values of the result. In addition, the PQR approach is more versatile when dealing with outliers and can effectively manage cases with unobserved heterogeneity.

V. PRESENTATION OF RESULTS AND ANALYSIS

➢ *Descriptive Statistics*

Table 2 presents the statistical properties of all variables used in this research study. The means of the food security index, human development index, technology adoption, agricultural output, population, inflation, gross fixed capital formation, and government effectiveness are 0.58, 0.55, 3.39, 17.56, 2.36, 9.85, 22.82, and -0.77, respectively. A survey of maximum values for the set of study variables, presented in a similar order, is as follows: 0.83, 0.81, 10.83, 47.81, 4.57, 557.20, 78.00, and 1.15. The period covered in the analysis of all variables spans from 2012 to 2023, encompassing forty-four (44) yearly observations across 43 countries. The variables with the highest and lowest records standard deviation values (variability) are the Agriculture and Food Security Index, with 11.29 and 0.08, respectively. The data attributes of skewness signify that the variables are positively skewed except for food security and population. Therefore, the data distribution shows a positively skewed (long tail to the right). The kurtosis direction of the data indicates that five of the eight variables (except FSI, HDI, and AGRIC) have scores above the threshold of three. Hence, the distribution is leptokurtic, representing a high peak with a broad base. The Jarque-Bera test of the distribution shows that all the variables (except FSI) have probability with values falling

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below 0.05. Hence, the Jarque-Bera values show that the null hypothesis of a normal distribution may be rejected. Therefore, the study data for this research work is not normally distributed. The nature of the data has implications for the study analysis and interpretation.

Table 2 Descriptive Statistics

	FSI	HDI	TECH	AGRIC	POPN	INFL	GFCF	GEFF
Mean	0.5812	0.5503	3.3966	17.5568	2.3595	9.8485	22.8197	-0.7674
Median	0.5905	0.5280	3.0900	18.3620	2.4823	4.7667	21.8257	-0.7975
Maximum	0.8301	0.8060	10.830	47.8132	4.5740	557.202	78.0009	1.1500
Minimum	0.3896	0.3520	0.0200	0.9956	-2.6174	-3.2334	2.1728	-1.9771
Std. Dev.	0.0833	0.1084	1.9684	11.0285	0.8501	33.7408	8.6343	0.5878
Skewness	-0.1239	0.4631	0.7883	0.2069	-1.0114	11.8413	1.3808	0.5715
Kurtosis	2.8954	2.3819	3.7948	2.0202	5.3530	167.593	9.1132	3.2881
Jarque-Bera	1.5518	24.434	42.992	24.2760	207.015	58188.6	961.816	29.872
Probability	0.4603	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	299.31	260.29	1124.3	9041.75	1217.52	4973.48	11706.5	-395.98
Sum Sq. Dev.	3.5623	5.5441	1278.6	62516.4	372.144	57375.7	38170.4	177.96
Observations	515	473	331	515	516	505	513	516

Source Authors' Computation

➢ *Correlation Matrix of Regressors*

Table 3 presents the results of the correlation test estimates for all the variables of the study. The variables with the highest correlations are AGRIC and FSI, and POPN and FSI, with correlations of 0.72 and 0.70, respectively, indicating positive relationships. The general results demonstrate that most of the variables have low negative correlation values. Hence, the trend of correlation values for all the variables of the study gives some assurance that the variables' distribution will not suffer from multicollinearity.

Table 3 Results of Correlation Analysis

Covariance Analysis: Ordinary								
Sample: 2012 2023								
Included observations: 326								
Correlation	**FSI**	**HDI**	**TECH**	**AGRIC**	**POPN**	**INFL**	**GFCF**	**GEFF**
FSI	1							
HDI	-0.3688	1						
TECH	-0.4784	0.4205	1					
AGRIC	0.7278	-0.4030	-0.2451	1				
POPN	0.7004	-0.5889	-0.5312	0.4220	1			
INFL	-0.0107	0.0134	-0.0574	-0.0692	-0.0576	1		
GFCF	0.0257	-0.0083	-0.1132	0.0002	0.2471	-0.1389	1	
GEFF	-0.4759	0.3785	0.4568	-0.3776	-0.3731	-0.1445	0.1081	1

Source Authors' Computation

➢ *Panel Unit Root Test*

The unit root test conducted utilises the ADF-Fisher and Levin, Lin & Chu methods. Table 3 presents the results of the unit root test, which specify that while FSI, HDI, and POPN have a unit root (not stationary) at the first difference (I (1), TECH, AGRIC, INFL, GFCF, and GEFF do not have a unit root (stationary) at the level (I (0). The panel cointegration test to be conducted will expect most of the variables to be stationary at I (1).

Table 4 Panel Stationarity Test Results

Variable	**ADF-Fisher**				**Levin, Lin & Chu**			
	@ Level		@ 1st Difference		@ Level		@ 1st Difference	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
FSI	122.201	0.0063	201.958	0.0000	-6.409	0.0000	-10.815	0.0000
HDI	123.981	0.0046	119.912	0.0092	-9.0951	0.0000	-7.4505	0.0000
TECH	72.5648	0.1688	130.475	0.0000	-4.2716	0.0000	19.0143	0.0000
AGRIC	94.6392	0.2456	206.349	0.0000	-4.3523	0.0000	-11.352	0.0000
POPN	110.48	0.0389	181.93	0.0000	-6.5559	0.0000	-36.349	0.0000
INFL	90.1822	0.3026	187.498	0.0000	0.6939	0.7561	-8.4979	0.0000
GFCF	91.0582	0.3340	223.904	0.0000	-3.9723	0.0000	-15.157	0.0000
GEFF	91.0582	0.3340	223.904	0.0000	-1.9562	0.0000	14.4387	0.0000

Source Authors' Computation

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> *Panel Cointegration Test*

All the variables of the study — HDI, TECH, AGRIC, POPN, INFL, GFCF, and GEFF — are subjected to the cointegration test. The Pedroni Residual approach to cointegration testing (Table 5) is employed to test for the long-run equilibrium relationship among the variables. The cointegration tests conducted show results indicating that, out of eight tests, five tests reject the null hypothesis of no cointegration among the study variables. Hence, the variables are cointegrated and there is a long-run equilibrium relationship among them.

Table 5 Panel Pedroni Cointegration Test

Pedroni Residual Cointegration Test				
Series: FSI HDI TECH AGRIC POPN INFL GFCF GEFF				
Null Hypothesis: No cointegration				
			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-3.8293	0.0000	-3.4912	0.0001
Panel rho-Statistic	7.4267	1.0000	-2.3874	0.0067
Panel PP-Statistic	-9.9857	0.0000	-13.3143	0.0000
Panel ADF-Statistic	0.8588	0.8102	-1.1302	0.1415

Source Authors' Computation

> *Panel Coefficient Impact Analysis*

- *GMM Regression Analysis*

The coefficient regression analysis is conducted using the panel GMM method, and the results are presented in Table 6. Six out of the seven explanatory variables have a significant impact on the food security index of African countries. While the effects of AGRIC, POPN and GEFF are positive and significant on the continent's food security index, the effects of HDI, TECH and GFCF are adverse and significant. The elasticity analysis reveals that a 1% change in HDI and TECH will result in a 0.46% and 0.03% change in food security, respectively, in the opposite direction. However, a 1% change in AGRIC, POPN, and GEFF will stimulate a 0.02%, 0.03%, and 0.01% change in food security in the opposite direction.

Table 6 Results of GMM Impact Analysis

Dependent Variable: FSI				
Method: Panel Generalized Method of Moments				
Instrument specification: C HDI TECH AGRIC POPN INFL GFCF GEFF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI	-0.4634	0.0383	-12.0978	0.0000
TECH	-0.0320	0.0120	-2.6325	0.0089
AGRIC	0.0200	0.0003	3.2185	0.0014
POPN	0.0292	0.0033	8.9751	0.0000
INFL	0.0100	0.0001	0.8717	0.3840
GFCF	-0.0006	0.0002	-2.6573	0.0083
GEFF	0.0112	0.0044	2.5185	0.0123
C	0.7826	0.0308	25.3826	0.0000
R-squared	0.8242	Mean dependent var		0.5847
Adjusted R-squared	0.8204	S.D. dependent var		0.0817
Durbin-Watson stat	0.1556	J-statistic		2.45E-21
Instrument rank	8			

Source Authors' Computation

- *Panel Quantile Regression Analysis*

The panel quantile regression analysis (PQA) is conducted in this study to compare and reinforce the GMM panel regression analysis that was executed in the earlier section. The quantile regression analysis results shown in Table 7 indicate that five out of the seven explanatory variables have a significant impact on the food security index of African Countries. The effects of AGRIC and POPN are positive and statistically significant on FSI, while the effects of HDI, TECH, and GFCF are adverse and statistically significant. However, the impact of AGRIC and GEFF is positive but insignificant. The elasticity analysis of the model shows that a 1% change in HDI and TECH initiates a 0.46% and 0.0% change in FSI, respectively, in the opposite direction. Additionally, a 1% change in AGRIC and POPN is accompanied by a 0.01% and 0.2% change in FSI, respectively, in the same direction. When the Quantile regression estimates are compared with the GMM regression output, it can be concluded that the effects of HDI and TECH are adverse and significant in affecting the FSI of African countries.

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Table 7 Results of Panel Quantile Regression Analysis

Dependent Variable: FSI				
Method: Quantile Regression (Median)				
Included observations: 326 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI	-0.4417	0.0448	-9.8530	0.0000
TECH	-0.0320	0.0160	-2.0215	0.0441
AGRIC	0.0108	0.0003	2.3597	0.0189
POPN	0.0233	0.0052	4.4598	0.0000
INFL	0.0010	0.0000	0.3306	0.7412
GFCF	-0.0005	0.0002	-2.0552	0.0407
GEFF	0.0007	0.0072	0.0991	0.9211
C	0.7783	0.0318	24.4384	0.0000
Pseudo R-squared	0.5632	Mean dependent var		0.5847
Adjusted R-squared	0.5536	S.D. dependent var		0.0817
Sparsity	0.0741	Quasi-LR statistic		589.3415
Prob (Quasi-LR stat)	0.0000			

Source Authors' Computation

➢ *Examining the Moderating Effect of Human Development and Technology Adoption on Food Security in Africa.*

The assessment of the interactive effect of HDI and TECH on the variation in FSI is conducted using GMM and Quantile Regression approaches, with the results shown in Appendices 1 and 2. While an examination by the Panel GMM shows a positive and significant effect of 0.0215, the estimation by Panel Quantile Regression shows a positive coefficient with a value of 0.0157 that is insignificant. While both assessments show a synergistic effect of HDI and TECH on FSI, the evaluation by GMM is significant, whereas the appraisal by PQR is not. Therefore, human development interacts with technology adoption to produce a positive effect on the food security status of African countries.

VI. CONCLUSIONS AND POLICY RECOMMENDATIONS

This study investigates the role of human development and technology adoption in enhancing food security in African countries. While examining specific contributions of human development and technology adoption, the study emphasises the synergistic contributions of both variables to the food security status of African countries. The data for the survey is sourced from 43 African countries, as well as the World Development Index (World Bank) and the ND_GAIN Country Index, covering the period from 2012 to 2023. The analytical framework employed in the study combines the Panel Generalised Method of Moments (GMM) and the Panel Quantile Regression (PQR) approaches. The specific findings of this research study are discussed below. First, the effect of human development on food security is negative and significant. It means that the level of human development skills and application in African countries has failed to impact the food security status of African countries positively. On a regular scale, the improvement in human capital development (HCD) is generally expected to enhance food security by fostering skills, productivity, and income. However, there are situations, such as in specific African contexts, where socioeconomic factors can lead to a negative relationship. For instance, some authors (Kaki et al., 2022) have argued that skilled labour shortages, skills mismatches, coupled with brain drain, could lead to a negative impact on human development and food security. In another related study, Iftikhar & Mahmood (2017) suggest that overinvestment in human capital development, while neglecting food production capabilities, can delay or weaken the gains in food security.

Second, the adoption of technology has a negative and significant impact on food security in Africa. This means that technology adoption in African countries has not improved the continent's food production capability. Technology adoption should enhance productivity and output in various sectors of an economy. It holds that technology is not inherently bad, but that without proper planning and institutions, technology adoption can create new risks and exclusions that leave a nation more food insecure. Many yield-raising technologies, such as improved seedings, controlled cultivation, and mechanised management, require the right labour skills, funding, and connectivity, which people with low incomes, low-level-skilled, remote farmers often lack (Aghughu et al., 2022; Abay, 2025). Additionally, the adoption of agricultural technology, including the use of improved seed varieties and other yield-enhancing inputs, can increase output. However, with increased exposure to global price volatility, the returns from agricultural output become very unstable and ultimately unattractive to the poor, rural local farmer. In addition, recent syntheses of agricultural inputs show fertiliser price shocks negatively transmit to farm margins and reduce food production (Bonilla-Cedrez et al., 2021).

Third, the interactive effect of human development and technology adoption on food security is mild, positive and significant. Both human development and technology adoption are at sufficiently good levels that their synergy can realistically and practically measurably improve food security. The synergy works well when the household acquires basic education and complements it with skills acquisition programs that incorporate technology content. Households become predominantly competent in applying technology-based inputs to enhance agricultural productivity.

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Human capital facilitates the farmer's capacity to assemble input complements in a timely manner, such as fertiliser use, input quality, and market participation (Davis et al., 2021). When improved agricultural varieties are adopted in conjunction with the right complements, there are significant gains in food availability and diet quality. Hence, educated/connected households' interfaces with technology to positively improve agricultural output.

➢ *Based on the Findings in this Study, the Following Policy Recommendations are Made:*

First, governments in African countries should improve investment in education and skills acquisition. The government should enhance agricultural education, technical skills, and entrepreneurial training through its programs. The focus should include enhancing farmers' capacity to adopt and effectively utilise modern technology. The education program should also consider the expansion of agricultural extension services and vocational training centres, as well as the integration of ICT skills into rural education curricula, to bridge the digital divide. As a follow-up, governments must consider offering scholarships and incentive schemes to youths to study agricultural sciences and agri-tech innovation. Second, extension of support to local farmers in various ways. Governments should keep in mind that over 50% of Africa's total agricultural output is produced by local farmers. Therefore, the government should focus on supporting local farmers through credit facilities and product-harvest guarantee schemes. The government should also extend training facilities to the local farmers and organise their access to high-yielding seeds.

Third, enhancement of agricultural research and development (R&D). Indigenous innovations that reflect local realities are more likely to promote sustainability and be easier for farmers to adopt. Governments should expand research services and increase budget allocations for agricultural research and development, as well as university–industry collaborations. Fourth, expansion of rural infrastructure and connectivity. The government should invest in roads to rural villages to enhance the marketability of rural products and increase the income of rural farmers. Physical and digital infrastructure are prerequisites for both human capital growth and technology adoption. Investment in rural roads, electricity, and internet connectivity will reduce transaction costs and improve access to inputs and markets.

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APPENDIX ONE

Table 1 GMM Analysis of the Moderated Effect of Human Development and Technology Adoption on Food Security in Africa

Dependent Variable: FSI				
Method: Panel Generalized Method of Moments				
Instrument specification: C HDI TECH AGRIC HDI*TECH POPN INFL GFCF GEFF				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI	-0.5576	0.0546	-10.2173	0.0000
TECH	-0.0150	0.0051	-2.9736	0.0032
AGRIC	0.0010	0.0003	3.1448	0.0018
HDI*TECH	0.0215	0.0089	2.4074	0.0166
POPN	0.0292	0.0032	9.0338	0.0000
INFL	0.0001	0.0001	0.9972	0.3194
GFCF	-0.0004	0.0002	-1.9341	0.0540
GEFF	0.0088	0.0045	1.9359	0.0538
C	0.8281	0.0360	23.0235	0.0000
R-squared	0.8274	Mean dependent var		0.5847
Adjusted R-squared	0.8230	S.D. dependent var		0.0817
S.E. of regression	0.0344	Sum squared resid		0.3744
Durbin-Watson stat	0.1612	J-statistic		0.0000
Instrument rank	9			

Authors' Computation

APPENDIX TWO

Table 2 GMM Analysis of the Moderated Effect of Human Development and Technology Adoption on Food Security in Africa

Dependent Variable: FSI				
Method: Quantile Regression (Median)				
Included observations: 326 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
HDI	-0.5275	0.1114	-4.7337	0.0000
TECH	-0.0112	0.0113	-0.9929	0.3215
HDI*TECH	0.0157	0.0216	0.7251	0.4689
AGRIC	0.0008	0.0004	2.0979	0.0367
POPN	0.0229	0.0056	4.1275	0.0000
INFL	0.0000	0.0000	0.4324	0.6658
GFCF	-0.0004	0.0003	-1.6262	0.1049
GEFF	0.0006	0.0069	0.0914	0.9272
C	0.8230	0.0681	12.0808	0.0000
Pseudo R-squared	0.5648	Mean dependent var		0.5847
Adjusted R-squared	0.5538	S.D. dependent var		0.0817
S.E. of regression	0.0351	Objective		4.2193
Quantile dependent var	0.5947	Restr. objective		9.6944
Sparsity	0.0730	Quasi-LR statistic		599.7106
Prob (Quasi-LR stat)	0.0000			

Authors' Computation