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Education, technology and agricultural transformation in Sub-Saharan Africa

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Abstract

Purpose – In developing countries, agriculture struggles with limited resources, poor infrastructure, and climate change impacts. Access to information technologies (IT) has become crucial for boosting production and resilience. However, farmers' lack of understanding of IT can negatively affect their food production. Thus, education is necessary to help farmers understand and use IT to improve their food production.

Design/methodology/approach – This study analyzes the role of education in the IT-agricultural production nexus in sub-Saharan African nations (SSA) using panel data on 34 countries over the period 2004-2020. The system generalized moments technique was used for the model estimation.

Findings – The results show that IT can be effectively complemented by education to enhance agricultural production. The thresholds of education needed for IT to increase agricultural production are provided. The established thresholds are as follows: (i) 0.651 for "fixed broadband," (ii) 0.476 for "internet," (iii) 0.538 for "mobile cellular subscription" and (iv) 0.489 for "IT." These findings suggest that the reinforcement of educational quality could help consolidate IT to enhance agricultural production.

Originality/value – This study complements the extant literature by examining the nexus between education and technology in the light of agricultural transformation in sub-Saharan Africa.

Keywords: Information technology, education, E-agriculture, Development

JEL Codes: O30, Q11, Q16

1. Introduction

In poor communities, agriculture is the main source of income for the population (Akpa et al., 2023). Similarly, agriculture plays a vital dual role in stimulating emerging nations' economies on the one hand and participating in poverty lessening on the other (Issahaku et al., 2018). Despite its critical position in emerging nations' economies, agricultural production remains low due to the low use of information technologies (IT). In addition, with a growing population, it is not impossible for SSA to suffer from food insecurity in the future (Oyelami et al., 2022). Therefore, to face food insecurity, it is essential to use and apply all available technologies, including IT, to achieve the desired agricultural transformation. Given the importance of IT in economies, particularly its contribution to labor productivity through evaluation and utilization, IT has received special attention (Lee & Brahmasrene, 2014; Pradhan et al., 2018; Sepehrdoust & Ghorbanseresht, 2019). Thus, to maximize the IT positive externality, different economic sectors, including agriculture, have exploited the rich occasions and possibilities created by evaluation and IT use (Ishida, 2015; Oyelami et al., 2022; Rohman & Bohlin, 2014). Indeed, in several nations, it significantly increases efficiency in different economic sectors (Bankole et al., 2013; Oyelami et al., 2022). To this end, many emerging nations are seeking to internalize IT to catch up quickly with their advanced counterparts. Indeed, for many emerging nations, the rapid adoption of IT-friendly policies is a major policy agenda (Oyelami et al., 2022; Pradhan et al., 2018), particularly for the agricultural sector.

In the agricultural sector, IT facilitates farmers' access to information in real time and encourages them to adopt new agricultural technologies, paving the way for agribusiness restructuring (Chandio et al., 2023). Moreover, agricultural production improvement allows farmers easy access to information on price diffusion, markets, and climate conditions. According to Chhachhar et al. (2014), one way for farmers to obtain agricultural information is through mobile phones and the Internet. For example, IT can be used by farmers to improve their technical knowledge and, in turn, to efficiently use production inputs, such as fertilizers and pesticides (Chandio et al., 2023; Hong et al., 2019; Lawin & Tamini, 2019). IT also has a major impact on the commodities market's structure and role, and on farmers' efficiency in these markets. Mobile phones improve communication between buyers and farmers, making markets more efficient and giving farmers easier access to markets. In addition, farmers' access to financial and agricultural services and input markets is facilitated (Munyegera & Matsumoto, 2018; Negi et al., 2018).

Empirical evidence has revealed that IT improves agricultural production (Chandio et al., 2023; Deng et al., 2022; Issahaku et al., 2018; Oyelami et al., 2022; Suroso et al., 2022). For example, Chandio et al. (2023) showed that in four Asian countries, namely the Philippines, Indonesia, Thailand, and Malaysia, that IT improves production in both the short and long term. Deng et

al. (2022) showed that IT positively affects green agricultural productivity in China, indicating that internet technology improves green agricultural productivity. Oyelami et al. (2022) showed that, in 39 sub-Saharan African countries, IT has a positive and significant effect on agricultural production. Suroso et al. (2022) showed that in 128 countries, IT has an overall positive and significant effect on the agricultural sector. Finally, Issahaku et al. (2018) showed that among smallholder maize farmers in Ghana, agricultural productivity was improved by IT use. In particular, the authors showed that at least 261.20 kg/ha were gained per production season by farmers who used IT (mobile phones).

Previous studies on the IT–agriculture nexus have shown that IT is beneficial for agricultural production (Chandio et al., 2023; Deng et al., 2022; Oyelami et al., 2022; Suroso et al., 2022). However, these studies have not investigated the channels through which IT can improve agricultural production. This study fills this gap by showing that education can serve as a channel through which IT can improve agricultural production. In fact, IT for farmers without basic education is of no use to them. However, as stated by Schultz (1961) and Becker (1962), education will empower farmers to use IT through the accumulation of skills and knowledge (Akpa, 2023 & Akpa et al., 2024). Indeed, farmers need continuous education to remain informed about the rapidly evolving advancements in technology, science, business management, and various other skills and domains impacting agricultural operations. This constitutes a contribution to the extant literature. The objective of this study is to explore the role of education in the IT-food production nexus in sub-Saharan Africa. However, it also responds to the following research questions:

- What is the effect of technology on agricultural production?
- At what education threshold can technology improve agricultural production?

With rising population, using technology is a key option to boost agricultural productivity, and education plays a vital role in enabling farmers to understand and adopt IT effectively. Therefore, this paper takes a new direction by showing that to break down the gap in agricultural production to feed the population increase, technology is as important as education. This research outcomes will benefit farmers, educators, policymakers, and community organizations. For farmers, it will enhance access to timely information (weather, markets, pest control) through IT adoption and promote digital and agricultural literacy for independent technology use. Educators can integrate digital agriculture into curricula and simplify complex technologies for local contexts. Policymakers can use the findings to design policies supporting digital literacy, rural education, and agri-tech infrastructure. Community organizations can raise awareness on digital tools and collaborate with institutions to provide hands-on training in local languages.

This study focuses on SSA because its population grew by 30.3% between 2012 and 2022, from 929.3 million to 1.21 billion, with an average annual growth of 3.03% (World Bank, 2024). To meet the rising food demand, African governments must adopt smart agriculture that leverages technology. Digital transformation in SSA faces major hurdles, including weak infrastructure, high connectivity costs, a persistent digital gender gap, low digital skills, and inadequate regulatory frameworks (World Bank, 2024). By end-2021, while 84% of SSA had 3G coverage and 63% access to 4G, only 22% used mobile internet. Broadband shows a similar gap, with 61% of people in range but not connected. High costs remain a key barrier: in 2019, 1 GB of mobile data cost 10.5% of monthly gross national income (GNI) per capita—far above the United Nations' 2% target. In 2021, a basic internet-enabled phone cost over 25% of monthly gross domestic product (GDP) per capita. In agriculture, SSA lags behind other regions in digitalisation (Okello et al., 2019; Choruma et al., 2024). By contrast, in the Global North, digital technologies support farm decision-making with real-time data. For example, China uses unmanned aerial vehicles (UAVs) for weed control (Wang et al., 2022), and Germany employs milking robots to save labor and time (Langer & Kühl, 2023).

Second, African nations are faced with food insecurity. According to Burchi et al. (2018), SSA remains the macro-region with the highest prevalence of hunger, and approximately 23.2% of the SSA population suffers from hunger. To address food insecurity in SSA nations, intelligent agriculture which involves technology adoption is required. However, agricultural technologies adoption is influenced by farmers' education level. Indeed, several studies have shown that education is crucial for agricultural technology adoption (Feyisa, 2020; Massresha et al., 2021; Zegeye et al., 2022). Agricultural knowledge in SSA is transmitted both informally through intergenerational learning and formally via institutions (Borda et al., 2023; Cassidy et al., 2019). While traditional practices dominate, formal training in universities and farm institutes has become vital with modern technologies (Cassidy et al., 2019; Cheesbrough, 1966). However, farmers' education levels remain low, with many being illiterate or only primary-educated (Kirui & Njiraini, 2019; Maré et al., 2025). This reflects challenges in SSA's education sector, including underfunding, poor infrastructure, limited access, and untrained teachers (Zickafoose et al., 2024; Wodon et al., 2018). Ilie & Rose (2016) further note wide disparities in educational opportunities across and within countries and among socioeconomic groups. Therefore, improving education and especially farmers' education will allow them to better understand technologies, use them, and improve agricultural production.

Third, in SSA, agriculture is central, providing livelihoods, especially in rural areas, and contributing significantly to GDP, exports, employments, poverty reduction and food security (OECD/FAO, 2016; Ritchie, 2022; Arshad, 2022). According to the World Bank (2024), agriculture

in SSA provides 51.57% of total employment and participates to 17.30% of GDP formation. Similarly, cereal production is increasing, moving from 135388507.6 metric tons in 2010 to 178594953.7 metric tons in 2021. However, SSA's agriculture faces multiple challenges notably limited mechanization, reliance on rainfed farming with low yields, climate change impacts, lack of diverse farming systems, financial constraints, inadequate research, high post-harvest losses, poor land management, and political instability that must be removed to promote smart agriculture (Akpa, 2024; Akpa et al., 2023).

Overall, the challenges in education, technology, and agriculture in SSA are deeply interconnected. Low farmer education hinders modern technologies adoption, keeping agricultural productivity low. Improving education equips farmers to adopt innovations like precision farming, improved seeds, irrigation, and digital platforms. Educated farmers are also better able to embrace sustainability, adapt to climate change, and engage in value chains. Thus, investing in farmer education is a strategic step toward boosting productivity, food security, and rural development.

The remainder of this paper is organized into four sections. Section two discusses the literature review, followed by section three which is devoted to the methodology. Section four interprets and discusses the estimation results, and the last section concludes with policy implications.

2. Theoretical and Empirical Review

2.1. Theoretical Review

The adoption of new technologies has been modelled by several researchers. The Technology Acceptance Model (TAM), introduced by Davis (1989), is a widely accepted framework for predicting user acceptance of new technology. Bawuah (2024) noted that the TAM has gained broad application and is recognized for its robust validity. Originating from the Theory of Reasoned Action (TRA) developed by Ajzen and Fishbein (1980) and Fishbein and Ajzen (1975), TAM suggests that individuals' perceptions shape their attitudes and behaviors towards a particular technology. TAM is centered on two primary constructs: perceived usefulness, which reflects a user's belief that a technology enhances job performance, and perceived ease of use, which measures the belief that using the technology requires minimal effort (Davis, 1989; Putri et al., 2023; Ndassi Teutio et al., 2021; Bawuah, 2024).

This study builds on the TAM by proposing that farmers' acceptance of technology is also influenced by their capacity to comprehend it. According to Schultz (1975), basic education enhances an individual's ability to recognize, clarify, and solve new problems. Welch (1970) elaborates that education impacts agricultural productivity through the "worker effect," which improves individual skills, and the "allocative effect," which enhances resource management abilities. However, less-educated farmers may be hesitant to adopt unproven technologies, often waiting until others have demonstrated profitability (Nelson & Phelps, 1966). This cautious approach affords educated farmers a "first-mover" advantage, making technology adoption more profitable and accelerating their uptake (Reimers & Klasen, 2013).

2.2. Information technology on food production

2.2.1. Direct effect of information technology on food production

Several studies have analyzed the link between different measures of IT (mobile phone subscription, Internet use, etc.) and agricultural production around the world. Chandio et al. (2023) analyzed the effect of IT (mobile phone subscriptions) on grain production in four Asian countries, namely Indonesia, Malaysia, the Philippines, and Thailand, and concluded that mobile phone subscriptions improve production in both the short and long term. Kaila and Tarp (2019) found that Internet access improved agricultural production in Vietnam. Chen et al. (2022) found that internet information positively affects rice production in the Yangtze River Basin in China. Deng et al. (2022) showed, based on panel data from 30 provinces in China between 1997 and 2019, that Internet technology positively affects green agricultural productivity, indicating that Internet technology improves green agricultural productivity. Zheng et al. (2021) analyzed the impact of Internet use on China's technical efficiency and

found that the technical efficiency of Internet users is greater than that of non-users. The findings also show that internet use positively affects the technical efficiency of banana production.

Chavula (2014) found in 34 African countries during the period 2000-2011 that despite the negligible impact of mobile phones, IT plays an important role in improving agricultural production, whereas mainline telephone lines still make an important contribution to agricultural development despite the widespread adoption of mobile technologies. Oyelami et al. (2022) found in 39 sub-Saharan African countries during the period 1995-2017 that mobile phone subscriptions and Internet use have statistically significant positive effects on agricultural production in sub-Saharan Africa over the long run. For the authors, IT needs to be accompanied by advisory services to raise awareness and educate farmers on the importance of continued adoption of IT infrastructure for agricultural practices in sub-Saharan Africa to improve agricultural production.

Issahaku et al. (2018) found that agricultural productivity was significantly improved by ownership and use of mobile phones. Indeed, mobile phones increased the productivity of farmers per production season by at least 261.20 kg/ha. The authors' findings also show that owning and using a mobile phone has a greater impact on productivity than does phone use alone. Ali et al. (2016) found that the impact of IT, including television, on agricultural productivity in Zambia was positive and statistically significant. The authors recommended the creation of an integrated agricultural information system and techniques. Mwalupaso et al. (2019) found a positive and significant relationship between mobile phone use and technical efficiency in Zambia.

Suroso et al. (2022) found that in both developed and developing nations, over the period 2012-2019 that there is an overall positive and significant effect of IT, such as fixed broadband subscriptions, Internet users, and secure Internet servers, on agricultural sector performance. Furthermore, the effects differ from one region to another for each IT indicator. The effect of the Internet on agriculture is positive in Africa, Asia, and Oceania. Similarly, agricultural sector performance is positively influenced by fixed broadband subscriptions and Internet access on agricultural sector performance by farmers located in emerging and developing economies. Eyike Mbong & Djoumessi (2024) found that mobile phone and internet coverage improve agricultural productivity in SSA.

Overall, previous studies have shown that information technology improves food production. However, they did not demonstrate that education plays an important role in understanding and accepting technology. Thus, this study builds on the existing research by examining

education as a moderating variable in the relationship between information technology and food production.

2.2.2. Indirect effect of information technology on food production, contingent on education

Most studies on the IT–agricultural production nexus have shown that IT improves agricultural production. However, these studies have failed to investigate the channels through which IT can improve agricultural production. This study fills this gap by showing that education can serve as a channel through which IT can improve agricultural production. In fact, IT for farmers without basic education is of no utility to them. However, as Schultz (1961) and Becker (1962) stated, education empowers farmers to use IT through the accumulation of skills and knowledge. Following Schultz's (1964) foundational work, the role of education in advancing agricultural development has been strongly emphasized. Education equips farmers with enhanced skills and productive capacities (Weir, 1999). Researchers such as Ninh (2021) further argue that education improves farmers' ability to access, interpret, and apply information, which empowers them to effectively address challenges in production, market dynamics, and financing. This capacity for information utilization allows educated farmers to implement more efficient solutions and make informed decisions, thus positively influencing agricultural productivity and resilience.

Several empirical studies have shown that education can improve agricultural production. For example, Ninh (2021) observed that in rural Vietnam, education positively impacts rice farming output by enabling farmers to manage larger farms more effectively and optimizing input combinations to enhance productivity. This finding contributes to the literature on the role of education in agricultural productivity. Similarly, Reimers and Klasen (2013) examined data from 95 developing and emerging economies and found that education boosts agricultural output, with higher returns on education in countries that are more technologically advanced. In Burkina Faso, Wouterse and Badiane (2019) also demonstrated that higher educational attainment correlates with increased agricultural production. In India, Paltasingh and Goyari (2018) highlighted that education benefits farmers who adopt modern technologies, suggesting that implementing farmer field schools alongside robust extension services could facilitate the broader dissemination of advanced farming techniques.

This study complements the extant literature by opposing Leng et al. (2020), Zhu et al. (2021), Suroso et al. (2022), and Chandio et al. (2023), who suggest that IT improves agricultural production. This study hypothesizes that IT improves agricultural production through educational channels. Figure 1 shows the schematic framework underlying the problem statement. Accordingly, as apparent in the figure, the impact of information technologies on food production is contingent on education, which is the moderating variable. The

acceptance of a technology by a farmer is based on their level of understanding. Thus, education can increase farmers' capacity to understand technology. Indeed, educated farmers adopt new technologies more than uneducated farmers do because they are able to perceive the expected gains that are greater.
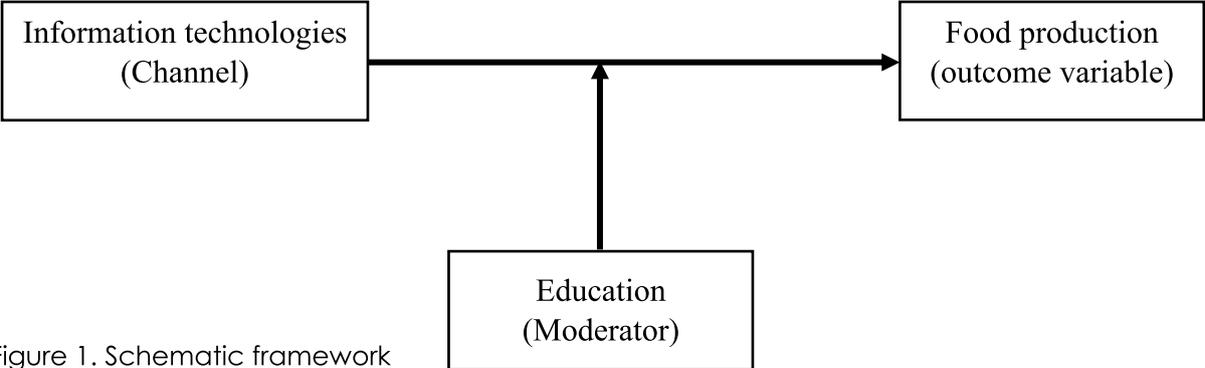
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┌──────────────────────┐                              ┌──────────────────────┐
│ Information technologies │ ──────────────────────▶  │   Food production    │
│      (Channel)        │              ▲              │  (outcome variable)  │
└──────────────────────┘              │              └──────────────────────┘
                                      │
                          ┌──────────────────────┐
                          │      Education        │
                          │     (Moderator)       │
                          └──────────────────────┘
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Figure 1. Schematic framework
Source: Authors' compilation

3. Methodology

3.1. Theoretical model

IT is an important tool in the agricultural sector owing to its ability to diffuse prices. Thus, to study the relationship between IT and agricultural production in sub-Saharan Africa, we used the Cobb Douglas production function, as it has been used in the literature to analyze the factors that influence agricultural production (Lio & Liu, 2008; Oyelami et al., 2022). Based on the assumption that production factors are paid for at their marginal productivity level, the Cobb-Douglas production function is as follows:

$$Y_{it} = f(A_{it}, K_{it}, L_{it}) \tag{1}$$

Where Y_{it} is the agricultural output represented by the agricultural value added of i in period t, K_{it} is the physical capital stock including land and fertilizer of i in period t,, L_{it} is the agricultural labor force of country i in period t, A is the level of technology represented by information technologies (IT).

Applying the logarithm to equation (1), we obtain the linear equation (2) that relates agricultural value-added, IT, and other variables that may influence agricultural production.

$$ln(Y_{it}) = \alpha_0 + \alpha_1 \ln(A_{it}) + \alpha_2 ln(K_{it}) + \alpha_3 ln(L_{it}) \tag{2}$$

With $(\alpha_1, \alpha_2, \alpha_2)$ representing the proportions of technology, capital, and labor, respectively, is used to obtain the level of agricultural output Y and is between zero and one; α_0 represents the model constant.

3.2. Empirical model

The empirical model chosen to analyze the transmission channel through which IT can affect agricultural production in sub-Saharan African countries is based on studies by Oyelami et al. (2022), Chandio et al. (2023), and Suroso et al. (2022). To capture the joint effect of education and IT, this study uses interactive estimation by including an interaction term (Education × IT) in the model. This approach reveals conditional or moderating effects that standard additive models may overlook. The empirical model takes the following form in equation (3):

$$ln(VAA)_{it} = \alpha_0 + \alpha_1 ln(VAA)_{it-1} + \alpha_2 ln(GDPC)_{it} + \alpha_3 EDUC_{it} + \alpha_4 IT_{it} + \alpha_5 FD_{it} + \alpha_6 ln(LAND)_{it} + \alpha_7 ln(LAB)_{it} + \gamma(EDUC_{it} \times IT_{it})_{it} + \varepsilon_{it} \tag{3}$$

Physical capital stock is measured by LAND, which represents arable and permanent cropland; EDU is human capital represented by the education index; LAB is agricultural labor force; VAA is agricultural value added; access to credit is measured by the variable FD, which refers to credit allocated to the private sector; the level of development is measured by the variable GDPC, which is the gross domestic product per capita; and information technologies are measured by variables such as fixed broadband subscription (FB), fixed telephone subscription (FT), internet user (INTERNET), and mobile cellular telephone (MO100). We also inserted the model IT index calculated using principal component analysis (PCA). Table 1 shows that the first principal component captures 66.2% of the variance across four IT indicators—fixed broadband, fixed-line phones, mobile phones, and internet access. Its retention is justified by the Kaiser criterion (eigenvalue > 1), with an eigenvalue of 2.647 (Tchamyou, 2020; Akpa & Gnidehou, 2025). $\alpha_0, \ldots, \alpha_7$ and ε_{it} are the coefficients to be estimated and the error terms, respectively. γ measures the conditional on a change in IT and education, simultaneously. i is the individual dimension (country) and t is the temporal dimension (year).

Table 1. Principal component analysis (PCA) for Information technologies (IT)

Principal components	Component matrix (loadings)				Proportion	Cumulative proportion	Eigen value
	Fixed broadband	Fixed-line telephone	Internet	Mobile cellular			
First PC	0.518	0.480	0.521	0.479	0.662	0.662	2.647
Second PC	0.442	0.551	-0.434	-0.559	0.245	0.907	0.979
Third PC	-0.494	0.537	-0.465	0.501	0.056	0.963	0.225
Fourth PC	0.540	-0.420	-0.569	0.456	0.037	1.000	0.149

Source: Authors' computation

In Equation (3), α_3 and α_4 capture the direct effect of education and information technologies, respectively, while α_4 refers to the simultaneous change in both education and information technologies on food production. Partially deriving Equation (3) relating to IT yields Equation (4), which is the IT unconditional effect on food production and the corresponding conditional impact of the interaction between IT and education:

$$\frac{\partial \ln (VAA)_{it}}{\partial IT_{it}} = \alpha_4 + \gamma EDUC_{it} \tag{4}$$

Equation (4) shows the net effect of IT, capturing its direct impact on the outcome after controlling for other variables, while excluding indirect (mediated through other variables).

Considering Equation (4), the corresponding education threshold is derived by taking the unconditional ratio absolute value to the conditional impact as follows:

$$\text{EDUC threshold} = \left|\frac{\text{unconditional impact}}{\text{Conditional impact}}\right| = \left|\frac{\alpha_4}{\gamma}\right| \quad\quad\quad (5)$$

Equation (5) captures the threshold effect of education, revealing non-linear relationships with IT and identifying critical education levels where its impact changes.

3.3. Estimation technique

Given that current agricultural output can be influenced by the previous period's output, we opted for the Generalized Method of Moments (GMM) for equation (3) estimation. For this, the dependent variable (agricultural output) is lagged by one period. This methodology has several advantages. For instance, the GMM (i) controls for the potential bias of endogeneity by lowering the error term's correlation with the endogenous variables (Akpa et al., 2025; Abdelghaffar et al., 2022; Asongu et al., 2020; Kim et al., 2018; Asongu & Nwachukwu, 2016); (ii) is most suitable when the number of individual dimension (N) exceeds the number of time dimension (T) (Abdelghaffar et al., 2022; Akpa et al., 2025; Asongu et al., 2020; Asongu & Nwachukwu, 2016); and (iii) eliminates bias due to unobserved country-specific effects (Akpa et al., 2025; Asongu et al., 2020; Asongu & Nwachukwu, 2016). Hence, the GMM system produces unbiased results because it assumes the absence of second-order autocorrelation and there is no relationship between error terms and instruments (Ababio et al., 2020; Abdelghaffar et al., 2022; Akpa et al., 2025). After running system GMM, diagnostic tests are required. The Arellano-Bond test checks for first-order autocorrelation, which is expected if the p-value is below 5%. Instrument validity is assessed with the Hansen or Sargan test; a p-value above 5% confirms instruments are valid and uncorrelated with the error term.

3.4. Data and sources

Data from multiple sources covering a panel of 34[1] nations from 2004 to 2020 were used to analyze the impact of IT on agricultural production as shown in Table 2. Only countries with complete data are included in the sample. The World Bank, FAO, and UNDP Development Indices are the data sources. The dependent variable used in the estimation was agricultural production, measured by agricultural added value. This variable choice is supported by the studies of Oyelami et al. (2022) and Suroso et al. (2022).

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[1] South Africa, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Côte d'Ivoire, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Kenya, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Uganda, Central African Republic, Democratic Republic of the Congo, Republic of the Congo, Rwanda, Senegal, Sudan, Tanzania, Togo, Zambia, Zimbabwe

The interest variable is information technologies, namely (i) fixed-line subscription to broadband, measured by the rate of fixed-line subscription to broadband per 100 inhabitants; (ii) fixed-line subscription to telephone, measured by the rate of fixed-line subscription per 100 inhabitants; (iii) Internet users, measured by the number of individuals using the Internet (as a % of the population); (iv) mobile cellular telephone, measured by the mobile telephone subscription rate per 100 inhabitants; and (v) information technology calculated by PCA and taken from the World Bank's development indicators. This variable choice is supported by studies conducted by Akpa (2023), Oyelami et al. (2022) and Suroso et al. (2022) The expected sign is positive, meaning that information technologies increase agricultural production in SSA.

Data on variables such as economic growth and financial development were taken from the World Bank's development indicators. Data on education are obtained from the UNDP database, and data on agricultural land area and agricultural labor are obtained from the FAO database. Economic growth is measured by growth in per capita domestic product and comes from the studies of Akpa (2023), Liu et al. (2020), and Enu and Attah-obeng (2013). The expected sign is positive, meaning that economic growth plays an important role in agricultural production. Financial development comes from Raifu and Aminu (2019) and Oliynyk-Dunn (2017), and the expected sign is positive, indicating that a developed financial sector improves agricultural production. The expected sign for education was positive. This means that increasing the education level increases agricultural production. This choice of the variable is supported by Akpa (2023), Liu et al. (2020), and Zakaria et al. (2019). The area of agricultural land was taken from the studies of Chandio et al. (2023) and Kaila and Tarp (2019), and the expected sign is positive, implying that an increase in agricultural land also increases agricultural production. The expected sign of agricultural labor is positive. This means that an increase in agricultural labor leads to an increase in agricultural production. The variables were sourced from the studies by Chandio et al. (2023) and Suroso et al. (2022).

The following table summarizes all variables used in the estimation, along with their measures and signs:

Table 2. Description of the explanatory variables

Variables	Measures	Sources	Signs
VAA	Agricultural production, measured by agricultural value added	WDI	
FD	Financial development, measured by domestic credit to the private sector by banks (% of GDP)	WDI	+/-
EDUC	Education index, measured by combined primary, secondary, and tertiary gross enrolment ratio	UNDP	+
FB100	Fixed broadband subscription, measured by the fixed broadband subscription rate per 100 inhabitants	WDI	+
FT100	Fixed-line telephone subscription, measured by the fixed-line subscription rate per 100 inhabitants	WDI	+
INTERNET	Internet user, measured by the number of individuals using the internet (as a % of the population)	WDI	+
MO100	Mobile cellular telephone, measured by the mobile telephone subscription rate per 100 inhabitants	WDI	+
IT	Information technology, measured by PCA	WDI	+
GDPC	Economic growth, measured by per capita domestic product	WDI	+/-
LAND	Arable and permanent cropland, in thousands of hectares	FAOSTAT	+/-
LAB	Agricultural labour force, measured by thousands of participants in an economically active population in agriculture	FAOSTAT	+/-

Source: Authors.

4. Results and discussion

4.1. Descriptive analysis of the data

Table 3 and Table 4 present respectively, the descriptive statistics and correlation matrix of the data used in the estimates. The average added value of the agricultural sector was 6660 million dollars, with a minimum value of 118 and a maximum value of 109000. This shows the heterogeneity among sub–Saharan African countries in terms of agricultural potential. On average, the private sector receives 19.641% of the GDP credit from the financial sector. The average combined education rate for primary, secondary, and tertiary education was 0.426. The average fixed-line broadband subscription rate per 100 inhabitants in the sample was 0.724. The average fixed-line subscription rate per 100 inhabitants is 2.417. The number of individuals using the internet as a % of the population was 12.016. The average mobile phone subscription rate per 100 inhabitants is 58.968. The economic growth per capita was 1917.202, with a minimum value of 128.337 and a maximum value of 11208.34. The difference between the maximum and minimum values shows a disparity in economic growth between the countries in our sample. The average area of cultivated land is 23614.66 ha with a standard deviation of 22247.49 showing that there is a disappearance of agricultural land for sowing among the countries in our sample. The agricultural labor force as a percentage of the population is 53.065, and the average rate of fertilizer use is 22.104.

Table 3. Descriptive statistics

Variables	Obs.	Mean	Std deviation	Min	Max
VAA (in million dollars)	562	6660	14800	118	109000
Financial development	547	19.641	17.544	0.007	106.260
Education	543	0.426	0.125	0.137	0.736
Fixed broadband	505	0.724	2.596	0	25.413
Fixed telephone	569	2.417	5.439	0	37.640
Internet	552	12.016	14.262	0.155	70
MO100	574	58.968	42.183	0.209	165.600
Economic growth	569	1917.202	2350.854	128.337	11208.340
Land	570	23614.660	22247.490	86	97608
Labour	544	53.065	20.840	4.600	90.620

Source: Authors.

The correlation test showed that there is a positive correlation between agricultural value-added and Internet use (0.121) and area of land sown (0.445), but a negative correlation between agricultural value-added and fixed broadband subscription (-0.080), fixed telephone subscription (-0.113), and agricultural labor force (-0.081). This means that if Internet use and sowing land area increase, the added agricultural value will also increase. Similarly, when fixed broadband subscriptions, fixed telephone subscriptions, and farm labor increased, farm value

added decreased. Table 4 also shows a positive correlation between the different technology variables. This justifies the fact that the different technology variables cannot be inserted simultaneously into the model, as this would create multicollinearity.

Table 4. Correlation test

	VAA	FD	EDU	FB	FT	INT	MO	ECO	LAN	LAB
VAA	1									
FD	-0.042	1								
EDU	0.025	0.515***	1							
FB	-0.080*	0.688***	0.403***	1						
FT	-0.113***	0.833***	0.413***	0.804***	1					
INT	0.121***	0.540***	0.485***	0.531***	0.419***	1				
MO	0.039	0.480***	0.448***	0.392***	0.340***	0.807***	1			
ECO	-0.014	0.673***	0.508***	0.565***	0.676***	0.604***	0.611***	1		
LAN	0.445***	0.185***	0.054	-0.094**	-0.053	0.151	0.089**	0.150***	1	
LAB	-0.081*	-0.626***	-0.408***	-0.421***	-0.586***	-0.612***	-0.662***	-0.738***	-0.165***	1

Source: Authors. (***$p<1\%$, **$p<5\%$ et *$p<10\%$)

4.2. Econometric analysis

Table 5 presents the results of the estimation using the system GMM estimation method. The estimated model is globally significant at the 1% level, as shown by the Fisher statistic. The lagged value of the agricultural value-added is significant at 1%, which shows that the agricultural value-added in the previous period is correlated with the current value and therefore justifies the persistence of the variable. The results also show that there is no second-order autocorrelation and that the Sargan/Hansen tests validate the instruments used.

Table 5. Econometric results (GMM system)

Variable	Dependent variable: Agricultural value added				
	Fixed broadband	Fixed telephone	Internet	MO100	IT
Log Agricultural value added (-1)	0.940*** (0.000)	0.738*** (0.000)	0.942*** (0.000)	1.032*** (0.000)	0.972*** (0.000)
Financial development	-0.007 (0.200)	-0.006 (0.188)	-0.004 (0.100)	-0.00002 (0.805)	-0.008*** (0.002)
Education	-0.695 (0.154)	-3.125** (0.013)	-1.388*** (0.009)	-1.046* (0.092)	0.126 (0.751)
Fixed broadband (FB)	-1.377** (0.018)				
Fixed telephone (FT)		-0.668*** (0.005)			
Internet (INT)			-0.061*** (0.001)		
MO100				-0.007** (0.020)	
Information Technologies (IT)					-0.691*** (0.003)
Education × FB	2.112**				

	(0.019)				
Education × FT		1.042***			
		(0.003)			
Education × INT			0.128***		
			(0.002)		
Education × MO100				0.013*	
				(0.089)	
Education × IT					1.411***
					(0.005)
Log economic growth	0.142***	0.381**	0.102**	0.0098***	0.132***
	(0.006)	(0.012)	(0.022)	(0.000)	(0.001)
Log Land	0.107**	0.216*	0.048*	0.016	0.068**
	(0.043)	(0.088)	(0.068)	(0.496))	(0.048)
Log Labour	0.221***	0.206	0.252**	0.098*	0.250**
	(0.005)	(0.141)	(0.049)	(0.060)	(0.022)
Constant	-1.031	1.916	-1.181	-1.011	-1.901*
	(0.357)	(0.258)	(0.789)	(0.148)	(0.970)
IT net effects	**-0.477**	**1.778**	**-0.037**	**-0.001**	**-0.089**
Education thresholds	**0.651**	**na**	**0.476**	**0.538**	**0.489**
AR (1)	-1.69*	-1.67*	-3.20***	-4.00***	-2.88***
	(0.091)	(0.095)	(0.001)	(0.000)	(0.004)
AR (2)	0.51	0.45	-0.19	-1.63	-0.02
	(0.608)	(0.489)	(0.848)	(0.104)	(0.987)
Sargan	6.90***	20.97**	13.72***	30.44	17.34***
	(0.864)	(0.051)	(0.319)	(0.002)	(0.137)
Hansen	19.61**	16.41***	19.96**	19.23**	21.24*
	(0.075)	(0.173)	(0.068)	(0.083)	(0.047)
Fisher	299600.27***	68573.71***	379521.04***	3.08e+06***	399056.44***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of instruments	21	21	21	21	21
Number of groups	34	34	34	34	34
Observations	423	466	457	467	415

Source: Authors (***p<1%, **p<5% et *p<10%)
Note: na means not applicable because net effects are positive

The findings showed that the IT index computed by PCA, and its indicators negatively and significantly influenced agricultural production. Overall, an increase in IT by one unit worsens agricultural production by 0.691%. Similarly, fixed broadband subscription, fixed line telephone subscription, internet users and mobile cellular telephone increase is accompanied by the decrease of agricultural production by 1.337%, 0.668%, 0.061% and 0.007%, respectively. These findings are unexpected in view of Leng et al. (2020), Zhu et al. (2021), Suroso et al. (2022), and Chandio et al. (2023), who concluded that IT enhances agricultural production. Similarly, the outcomes show that an increase in education decreases agricultural production by 3.125%, 1.388% and 1.046% when fixed line telephone, internet and mobile cellular telephone are inserted in the equations. In interactive estimations, the IT unconditional estimate should not be interpreted in isolation, which is why net effects and thresholds are calculated in the following paragraph. Furthermore, the interaction between IT indicators and education showed that all the interactions were significant and positive. Indeed, simultaneous growth in both IT indicators,

such as fixed broadband, fixed telephone, internet, mobile cellular subscription, and the information technology index, and education enhances agricultural production. In short, the findings support the argument that education can serve as a catalyst for decreasing the gap between IT and agricultural production in SSA nations. These findings are similar to those of Liu et al. (2020), Anik et al. (2017), and Zakaria et al. (2019), who found that agricultural productivity improved with an increase in human capital in South and Southeast Asian nations and align with Schultz (1975) who posits that basic education improves an individual's capacity to identify, analyze, and address new challenges, including technology adoption.

To evaluate the global impact of education on modulating the influence of IT on agricultural production, the net effects and thresholds were calculated. Equivalent net effects and thresholds involve both unconditional and IT conditional effects on agricultural production. For example, in the fourth column of Table 5, in the regressions referring to mobile cellular subscription, the mobile cellular subscription net effect from education in moderating the IT effect (mobile cellular subscription) on food production is –0.001 ([-0.007]+ [0.013× 0.426]). In the calculation, 0.426 is the education mean value; the unconditional effect of mobile cellular subscription is -0.007, while the conditional effect from the interaction between mobile cellular subscription and education is 0.013. This approach to determining the total incidence based on net effects is reliable with the current interactive estimation literature (Asongu & Odhiambo, 2020b, 2020a; Tchamyou & Asongu, 2017). Reliable with Asongu & Odhiambo (2020b), the corresponding education thresholds were calculated which are: (i) 0.651 (i.e. 1.377/2.112) for "fixed broadband," (ii) 0.476 for "internet," (iii) 0.538 for "mobile cellular subscription," and (iv) 0.489 for "IT." The associated thresholds were obtained by dividing the unconditional effect by the conditional incidence, as described in Equation (5).

In view of the above, the calculated education thresholds are education levels that should be reached for education to moderate IT to generate a global positive influence on agricultural production. Hence, although the net effects of IT on agricultural production are negative, the related global influence on agricultural production is positive when education levels are beyond the established education thresholds. To put this in more perspective, let us consider the same example used above for the net effect calculation to better express the importance of the "mobile cellular subscription" threshold of 0.476. Therefore, once "education" is above the threshold of 0.476 (e.g. 0.576), the IT (mobile cellular subscription) global influence on agricultural production moves from negative to positive or 0.0004 ([-0.007]+ [0.013× 0.576]). Therefore, it is suggested for policy makers to articulate and implement policies that allow "education" level in the nation to be above 0.476 for the mobile cellular subscription estimated profits in terms of food production to be realized. These details can be extended to other established educational thresholds.

Access to credit is very important for activity development, especially agricultural activities, as it enables farmers to access technology and agricultural inputs. The results show that financial development negatively affects agricultural value-added, but only the outcomes for IT index are significant. A 1% increase in financial development reduces agricultural production by 0.008%, suggesting the financial sector provides little credit to farmers due to high risks from climate dependence, leading to credit constraints that limit farmers' access to loans. These results are consistent with Dong et al. (2012), who showed that removing credit constraints would improve agricultural productivity by 75%. The results are also consistent with Zakaria et al. (2019), who found an inverted U-shaped relationship in South Asia, meaning that above a certain threshold, financial development reduces agricultural production. According to the authors, this result is explained by the fact that if financial development increases further, the amount of credit is used for other purposes, such as industrialization, and not for agricultural production. In contrast, Chandio et al. (2023) and Omoregie et al. (2018) showed that the financial sector is very important for agricultural production in China and Nigeria, respectively. These findings support Stiglitz & Weiss (1981), showing that imperfect information causes lenders to struggle identifying borrower risk, often denying rural farmers credit even at higher rates, which leads to underinvestment and limits agricultural productivity.

The analysis reveals that economic growth per capita improves agricultural value-added. A 1% increase in per capita economic growth results in an increase in agricultural value-added ranging between 0.284% and 0.493%. This finding supports the premise of the classical growth theory, which argues that economic development enables greater accumulation of capital, including in the agricultural sector. This outcome aligns with Chandio et al. (2020), who also observed that economic growth improves agricultural value-added. Moreover, this result is consistent with endogenous growth theory (Romer, 1986; Lucas, 1988), which emphasizes the role of human capital, innovation, and technological progress as key drivers of sustained growth. Thus, higher per capita incomes can enhance investments in agricultural education, extension services, and IT, creating a virtuous cycle between economic and agricultural development. However, contrasting evidence from Liu et al. (2020) suggests a negative relationship between economic growth and total agricultural factor productivity, potentially explained by structural transformation theory (Lewis, 1954).

The analysis demonstrates that the sowing land area improves agricultural value-added. Specifically, a 1% increase in the sowing area results in an increase in agricultural value-added of approximately 0.104% to 0.195%. This finding indicates that as the most fertile lands are exhausted and soil fertility declines, farmers often respond by expanding cultivation into marginal or less fertile lands. This relationship is supported by Gul et al. (2022) and Zhang et al.

(2022), who found that an increase in cultivated area directly translates into higher agricultural output, particularly in contexts where agricultural intensification remains limited. From a theoretical perspective, this outcome can be linked to the Ricardian theory of rent (Ricardo, 1817), which posits that as demand for agricultural production rises, cultivation extends to less fertile lands, leading to diminishing marginal returns.

The analysis reveals that agricultural labor imrpoves agricultural value-added. Specifically, a 1% increase in agricultural labor leads to an increase in agricultural value-added ranging from 0.251% to 0.867%. The results align with Suroso et al. (2022), Zhang et al. (2022), and Chandio et al. (2023), who demonstrate that labor input remains a significant determinant of agricultural productivity, especially in contexts where mechanization and capital-intensive technologies are limited. However, Chandio et al. (2020) present contrasting evidence from China, showing that agricultural labor negatively affects production in the short run due to labor surpluses and underemployment, but contributes positively in the long run as structural transformation reduces labor redundancy and increases labor productivity. From a theoretical perspective, these findings are closely related to the Cobb-Douglas framework (Cobb & Douglas, 1928), where labor is a key factor of production alongside land and capital.

5. Conclusion and implications

IT plays a very important role in the agricultural production sector because, through their various services, they facilitate the dissemination of prices, access to market and weather conditions, the implementation of new farming techniques, and increase farmers' technical knowledge, which enables them to use production inputs such as fertilizers and pesticides more efficiently. The objective of this study is to analyze the effect of IT on agricultural production in SSA. To do so, we built a database of 34 SSA countries based on World Bank Development Indicators, FAO, and UNDP databases from 2004 to 2020. We also calculated an IT index based on four indicators and estimated a panel data model by adopting the GMM in system.

These findings indicate that IT can be effectively complemented with education to enhance agricultural production. The thresholds of education needed for IT to increase agricultural production are provided. The established thresholds are as follows: (i) 0.651 of "fixed broadband," (ii) 0.476 for "internet," (iii) 0.538 for "mobile cellular subscription" and (iv) 0.489 for "IT." Other drivers of agricultural production include financial development, economic growth per capita, agricultural land, and agricultural labor. While financial development negatively influences agricultural production, economic growth per capita, agricultural land, and labor improve agricultural production. This study findings suggest that the reinforcement of educational quality could help consolidate IT to enhance agricultural production.

5.1. Policy implications

The low use of IT is a key factor in explaining the low agricultural production in developing countries. Thus, increasing IT use in agriculture can improve agricultural productivity. However, the results from this study support the argument that IT alone is not sufficient to promote agricultural production in SSA nations but that they need education. Policies geared toward strengthening the quality of education in SSA nations could help consolidate IT infrastructure, which will help achieve the desired level of agricultural production and generate productivity gains for the economy. IT is crucial in the economic sphere, particularly for agricultural output. Therefore, to foster a beneficial relationship between IT and agricultural production, SSA nations need to strengthen their policies to raise educational standards, particularly above the set educational criteria. Therefore, the quality of IT usage can be improved by investing in IT infrastructure through high-quality education, which will benefit agricultural production. Low-quality IT hinders the growth of agricultural production. Policies must be taken to liberalize the GSM market, which in Africa is composed of very few operators and therefore makes internet services expensive despite its poor-quality. By putting these suggestions into practice on an economic level, SSA nations will be able to boost agricultural output and create enough revenue to advance their economies. Socially, it will help fulfill Sustainable Development Goals 1, 2, and 9 in addition to guaranteeing food security. Similarly, this study expands the TAM by

highlighting education as a key factor in technology adoption, alongside perceived usefulness and ease of use. Education improves individuals' ability to understand and use new technologies. Practically, African governments should reform education by creating agricultural schools and training centers that include digital tech, climate-smart farming, and agribusiness to prepare farmers and youth for modern, resilient agriculture.

5.2. Limitations

This current research is not without limitations that constitute a room for futures research. The limitation of this study is that it does not consider the role that country-specific economic development fundamentals can play in the corresponding nexuses. Future studies will therefore analyze how the fundamentals of economic development specific to each country influence the corresponding nexuses.

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