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A Multisectoral Systems Analysis of Digital Engagement and Agricultural Productivity in Sub-Saharan Africa

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ABSTRACT

Background: Intersectoral synergies between technology, environment and farming are vital for sustainable agricultural development. This requires innovative solutions to overcome low productivity and environmental stress; digital technologies offer potential to transform smallholder agricultural systems.

Methods: This study evaluates the sustainability impacts of digital engagement (DE) in Sub-Saharan African agriculture through a systems-based assessment framework. Using Partial Least Squares-Structural Equation Modeling (PLS-SEM) on World Bank datasets (2000-2023), this research quantifies DE's effects on agricultural productivity while accounting for critical moderators: environmental stress, feasibility assessment (FA), technical skills (TS) and livestock farming (LF).

Result: Results reveal significant positive interactions, with coefficients of 1.690 for natural environment (NE), 2.387 for FA, 3.901 for TS and 77.202 for LF, demonstrating the moderating role of environmental performance between DE and agricultural productivity. The findings contribute to impact evaluation methodologies by demonstrating how PLS-SEM can assess complex technology-environment interactions, while providing actionable criteria for appraising digital agriculture projects in resource-constrained settings. However, challenges such as inadequate infrastructure and limited farmer technical skills must be addressed. By bridging digital innovation with environmental stewardship, this research offers actionable insights for policymakers to advance sustainable agricultural practices in resource-constrained settings.

Key words: Agricultural productivity, Digital engagement, Environmental sustainability, Partial least squares-structural equation modeling.

INTRODUCTION

The global population is projected to exceed 10 billion by 2050, intensifying pressures on food security, resource efficiency and environmental sustainability. In Sub-Saharan Africa (SSA), agriculture is a cornerstone of livelihoods and economic development, yet the sector faces acute challenges, including climate change, resource inefficiencies and limited access to modern technologies (Giacomo *et al.*, 2021).

Rapid population growth affects the sustainable development and challenges the quality of human life in various forms including threatening food security, increasing unemployment, putting more pressure on the healthcare system, stress on infrastructure, environmental issues and increasing the demand for resources (Filipenco, 2024). To address these challenges, experts have focused on modernizing sectors through improved methods for goods production (Mohamed *et al.*, 2022). Digital engagement (DE), such as internet connectivity and digital tools, offers transformative potential for these issues by enhancing environmental stewardship and agricultural productivity (Hamad and Jia, 2022; Mathew *et al.*, 2023).

According to previous literature, modern techniques, such as intelligent and automated systems, can boost productivity (Sander *et al.*, 2021). However while previous research has examined digital engagement in developed contexts (Smidt and Jokonya, 2021). A significant gap remains in understanding how environmental factors moderate DE's effectiveness in SSA's unique agricultural systems. Specifically, studies have not adequately

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[1]https://news.un.org/en/story/2024/07/1151971#

addressed: The role of environmental stress as a moderator, longitudinal impacts on sustainable intensification and the feasibility-assessment framework for DE implementation in resource-constrained settings. This research addresses these gaps by analyzing DE in 45 SSA countries while examining critical moderating factors.

Overall, the study's objectives are: to emphasize DE's implications for agricultural productivity and sustainable practices and to explore how DE can promote environmental stewardship, resource efficiency and resilience in SSA's agricultural sector. This analysis addresses the following research questions: What are the measurable productivity and sustainability impacts of DE in SSA agriculture, how do environmental factors moderate these effects? And what policy and project design principles emerge to optimize DE's sustainability impacts in smallholder farming systems?

This investigation combined Partial Least Squares-Structural Equation Modeling (PLS-SEM) to empirically analyze the complex relationships involved, treating DE as the main latent variable and sustainable agricultural production as both latent and explanatory variables. The findings highlight DE's potential to enhance resource efficiency and reduce environmental harm, though infrastructural and educational barriers persist. The results provide actionable insights for policymakers and practitioners, emphasizing the need for targeted interventions to support DE in rural SSA.

Literature review

The transition from traditional to modern agricultural practices represents a fundamental shift necessary for achieving sustainable productivity gains across SSA. This transformation increasingly relies on DE, the integration of internet-based technologies, mobile platforms and connected digital tools into agricultural value chains (Martínez *et al.*, 2022). Where previous research focused narrowly on specific technologies like virtual reality (Chakrapani and Kalpana, 2025) this study examines the broader paradigm of DE and its systemic interactions with environmental and agricultural systems. The agricultural sector in SSA faces unique challenges that DE may address, including fragmented knowledge systems, limited extension services and climate vulnerability.

Environmental performance critically moderates DE's effectiveness, particularly in water-stressed systems where ecosystem services and climate patterns shape technology adoption. Using various methods, numerous studies have explored the strength and potential of DE in modernizing the agricultural sector (Vyas and Singh, 2022; Kumari *et al.*, 2023). However, DE in agriculture refers to the introduction of computers and technology for the implementation of smart agriculture practices and agroecology training (Dayıoğlu and Turker, 2021; Kumari *et al.*, 2021). Some scholars have used PLS-SEM to evaluate the major constraints that influence the individual decision to adopt blockchain technology in smart agriculture in developed countries (Ullah, 2021). DE integrates digital technologies into traditional farming, drawing from multiple disciplines and requiring digital literacy investments to enhance agricultural understanding and training.

This study builds on existing literature by examining the impact assessment of DE and environmental sustainability in SSA's agricultural context. The conceptual framework, validated through PLS-SEM in Fig 1 integrates these multidimensional relationships, positioning DE as both driver and outcome of sustainable agricultural transformation. Unlike narrow technology adoption models, this framework accounts for the recursive relationships between digital tools, farmer capabilities and environmental conditions. Internet connectivity serves as the foundational layer enabling DE, while agricultural production systems and natural resource bases determine its ultimate impacts.

Methodologically, this study advances beyond prior research by employing PLS-SEM to analyze DE's systemic interactions. Previous studies often treated digital technologies as isolated inputs rather than embedded components of complex socio-technical systems (Koyu *et al.*, 2022). The current approach captures both direct effects (*e.g.*, yield improvements from digital extension) and indirect pathways (*e.g.*, environmental co-benefits from optimized input use).

Digital engagement enables agricultural monitoring through mobile and cloud platforms, integrating agricultural science with information technologies. Consequently, DE contributes significantly to sustainable agricultural production (SQAP) (Hypothesis 1).

Besides, effective digital engagement requires reliable infrastructure, while environmental factors influence both connectivity and agricultural data relevance. Thus, the natural environment significantly moderates the relationship between DE and agricultural outcomes (Hypothesis 2).

Prior to implementing DE solutions in livestock farming, thorough feasibility assessments must evaluate infrastructure readiness, electricity access, cost-benefit ratios and community willingness to adopt new technologies (Sangapate *et al.*, 2024). Therefore, this study proposes that feasibility assessment of digital infrastructure significantly moderates DE adoption in livestock systems (Hypothesis 3).

Farmer competencies, particularly technological proficiency and adaptability, are critical for successful digital engagement in agriculture (Higgins *et al.*, 2017). These findings confirm that technical skills are essential for optimizing agricultural techniques through digital means (Hypothesis 4).

Comprehensive DE adoption in livestock farming enhances management efficiency across feeding, breeding and health monitoring systems (Anastasiou *et al.*, 2023).

These contribute to more sustainable agriculture practices (Hypothesis 5).

These hypotheses collectively provide a framework for examining how digital engagement interacts with environmental, infrastructural and human capital factors to influence sustainable outcomes in SSA.

MATERIALS AND METHODS

Data and study area

Conducted at the management science and engineering research station of China Three Gorges University in 2025, this study analyzes panel data from 45 SSA countries (2000-2023). Countries are stratified by income level (low, lower-middle, upper-middle) to account for development disparities. Table 1 displays the descriptions and data sources of all the indicators. To ensure the results validity and reliability, data underwent rigorous cleaning for missing values, outliers and multicollinearity. Variables were log-transformed to normalize distributions. The study employs a two-stage PLS-SEM approach to assess both the measurement quality and structural relationships of DE's impact on agricultural systems.

DE is operationalized using internet users per 100 people, reflecting connectivity penetration critical for digital agriculture tools. This proxy aligns with empirical studies demonstrating internet access as the foundational layer for broader DE adoption (Lv, 2019). While internet users per 100 people provides the most consistent cross-national metric for digital infrastructure readiness, this proxy has limitations. It does not capture qualitative aspects of digital engagement such as usage intensity, digital literacy levels, or the purpose of internet use. Prior research confirms internet penetration strongly predicts adoption of advanced agricultural technologies (Trendov *et al.*, 2019).

Direct effects model

The hypothesized direct path in the first equation (1) tests the positive relationship between DE and its impact on agricultural outcomes efficiency.

$$\ln DE_{it} = \alpha_i + \gamma_t + \beta_1 \ln SQAP_{it} + \beta_2 \ln FA_{it} + \beta_3 \ln TS_{it} + \beta_4 \ln LF_{it} + \beta_i \text{Control} + \varepsilon_{it} \quad \text{...(1)}$$

Where,

- $\ln DE_{it}$= The digital engagement.
- α= The constant or the country-fixed effect.
- γ= The time-fixed effect.
- $\ln SQAP_{it}$= The sustainable quality in agricultural production.
- $\ln NE_{it}$= The natural environment.
- $\ln FA_{it}$= The FA.
- $\ln TS_{it}$= Technical skills.
- $\ln LF_{it}$= The feasibility assessment measurement.
- The path coefficients β represent the direct and moderating effects of SQAP, NE, TS, FA and LF on DE.
- Control combines the control variables.
- The error terms ε_{it} captures unexplained variance in the model.

The second equation (2) tests reverse causality pathways.

$$\ln SQAP_{it} = \alpha_i + \gamma_t + \theta_1 \ln DE_{it} + \theta_2 \ln FA_{it} + \theta_3 \ln TS_{it} + \theta_4 \ln LF_{it} + \beta_i \text{Control} + \varepsilon_{it} \quad \text{...(2)}$$

Where,

- The path coefficients θ represent the direct and moderating effects of VRI, NE, TS, FA and LF on SQAP.
- Control combines the control variables.
- The error terms captures unexplained variance in the model.

Moderated effects model

The hypothesized Moderating Effect is shown in the third equation (3), more precisely, natural Environmental (NE) moderates the relationship between DE and agricultural outcomes. This model aims to demonstrate if higher environmental performance enhances the positive impact of DE on sustainable farming practices.

$$\ln DE_{it} = \alpha_i + \gamma_t + \sigma_1 \ln SQAP_{it} + \sigma_2 \ln NE_{it} + \sigma_3 \ln FA_{it} + \sigma_4 \ln TS_{it} + \sigma_5 \ln LF_{it} + \mu(\ln SQAP_{it} \ln NE_{it}) + \tau(\ln SQAP_{it} \ln FA_{it}) + \delta(\ln SQAP_{it} \ln TS_{it}) + \omega(\ln SQAP_{it} \ln LF_{it}) + \alpha_i \text{Control} + \varepsilon_{it} \quad \text{...(3)}$$

Where,

- The interaction terms μ, τ, δ, τ and show the combined impact of SQAP with NE, TS and FA on DE.
- Control combines the control variables.
- The error terms ε_{it} captures unexplained variance in the model.

The formula in (4) assesses the collinearity level among the formative indicators.

$$VIF = \frac{1}{1 - R_i^2} \quad \text{...(4)}$$

Where,

- VIF= The variance inflation factor of each item.
- R^2= The R-squared value from the main regression analysis result.

RESULTS AND DISCUSSION

Descriptive statistic

The summary statistics in Table 2 report a total sample of 1,080 observations. It has been noticed that all selected variables have a positive average value with a considerably uniform distribution. The lower standard deviation provided by this table implies less variability in this study dataset. Before proceeding with data analysis, normality has been checked using skewness and kurtosis results in Table 2.

Measurement model assessment

The PLS-SEM analysis result in Table 3 reveals significant insights about digital engagement's role in sustainable agriculture across SSA. Direct path analysis reveals significant positive coefficients ($p<0.01$), confirming H1 that digital engagement (DE) strongly enhances sustainable agricultural production (SQAP). This demonstrates DE's potential to improve production quality and motivate adoption of modern techniques in rural agriculture. These results

support scholars that highlights the positive efficiency among the DE and agricultural production interrelationship (de Oliveira and Corrêa, 2020; Bernard *et al.,* 2021) also confirm that information and communication technologies (ICT), including internet access, can enhance agricultural productivity and rural development, particularly in SSA (Bernard *et al.*, 2021; Effiong and Iheme, 2024). The direct path coefficient of -0.715 between DE and SQAP initially suggests a counterintuitive negative relationship. This aligns with Rede G.D. and his colleague's research about the impact of micro-irrigation technologies where initial productivity declines often occur during the learning and implementation phase of new digital tools (Rede *et al.*, 2024).

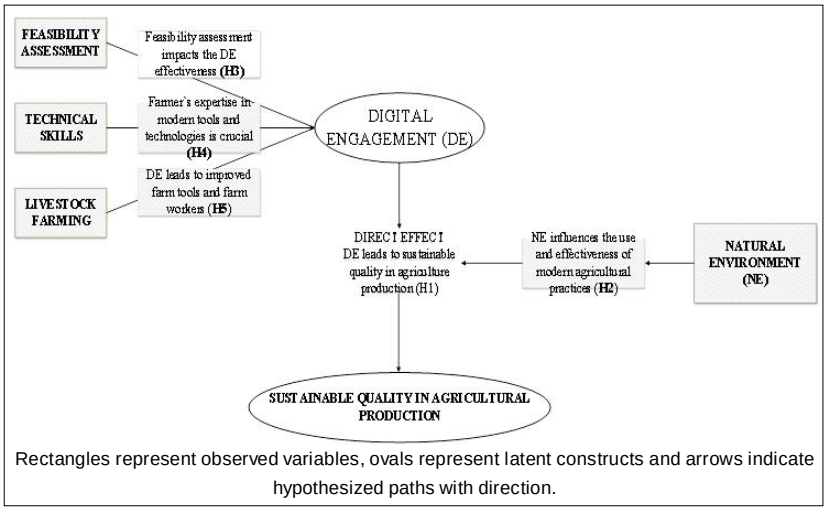


Fig 1: Conceptual PLS-SEM model showing hypothesized relationships between digital engagement (DE), sustainable agricultural production (SQAP) and moderating variables (NE, FA, TS, LF).

Table 1: Variable descriptions and sources.

Core variables	Explanatory variables	Variable and units	Sources
Latent variables	Digital engagement (DE)	Internet users (per 100 people)	International Telecommunication Union, World Telecommunication/ICT Development Report and Database. https://databank.worldbank.org/home
	Sustainable quality in agricultural production (SQAP)	Crop production index (2014-2016 = 100)	FAO https://www.fao.org/faostat/en/#data
Construct variables	Livestock farming (LF)	Livestock production index (2014-2016 = 100)	https://databank.worldbank.org/home
	Technical skills (TS)	School enrollment, educational level in rural area: Primary and secondary, gender parity index (GPI)	
	Feasibility assessment (FA)	Access to electricity, rural (% of rural population)	
Moderator	Natural environment (NE)	Level of water stress: Freshwater withdrawal as a proportion of available freshwater resources	
Control variables	Control	GDP per capita (US current dollar)	
		Rural population (% of total population)	
		Improved water source (% of population with access)	
		Agroforestry and fishing (annual % growth)	
		Agricultural land (% of land area)	

Table 2: Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
DE	1,080	9.774	11.723	0.006	51.919	1.722	5.578
SQAP	1,080	90.808	25.700	4.352	183.450	-0.670	4.853
NE	1,080	12.232	21.736	0.027	118.656	3.320	14.958
FA	1,080	20.911	23.7655	0.159	100.000	1.621	5.121
TS	1,080	0.891	0.144	0.537	1.996	0.503	10.885
LF	1,080	1156732.000	7788273.000	25.58	5.99e+07	6.627	45.230
GDP per capita	1,080	1847.055	2472.639	110.461	19849.720	3.061	15.173
Rural pop	1,080	59.458	18.736	1.092	91.754	-0.919	4.015
Water source	1,080	68.988	16.55415	23.5000	99.900	-0.122	2.265
Agri land	1,080	46.518	20.487	3.667	81.892	-0.212	2.240
Agroforestry	1,080	21.020	13.216	0.893	79.042	0.670	3.872

Table 3: Multiple regression analysis of the path model.

Variables	Model1 DE	Model 2 SQAP	Moderating path
SQAP	-0.152***		-0.715***
	(0.040)		(0.081)
NE			-0.628***
			(0.231)
FA	0.257***	-0.114***	-0.306***
	(0.036)	(0.028)	(0.118)
TS	-0.253***	0.174***	-0.979***
	(0.062)	(0.048)	(0.166)
LF	3.925***	-1.191***	2.063**
	(0.368)	(0.298)	(1.009)
c.SQAP#c.NE			1.690**
			(0.727)
c.SQAP#c.FA			2.387***
			(0.541)
c.SQAP#c.TS			3.901***
			(0.886)
c.SQAP#c.LF			77.202**
			(32.524)
Rural pop	-0.879***	0.564***	-0.597***
	(0.138)	(0.107)	(0.140)
GDP per capita	0.445***	0.019	0.411***
	(0.059)	(0.047)	(0.057)
Improved water source	-0.289***	0.487***	-0.108
	(0.074)	(0.056)	(0.076)
Agri land	-0.123	0.422***	-0.087
	(0.132)	(0.102)	(0.127)
Agro forestry	-0.074	0.131***	-0.014
	(0.054)	(0.042)	(0.054)
		(0.024)	
Constant	0.283***	-0.169***	0.298***
	(0.042)	(0.033)	(0.041)
Observations	1,080	1,080	1,080
R-squared	0.777	0.650	0.797
Number of country	45	45	45
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Natural environment significantly moderates DE's effectiveness (β = 1.690), with strongest synergies under moderate water stress (25-40%). This supports H2 and aligns with previous literature, confirming DE acts as an adaptive mechanism where timely information improves resource management, though ecological limits constrain benefits in extreme stress (Dabrowski *et al.*, 2009; Vasilii *et al.*, 2024).

Analysis confirms FA (2.287), TS (3.901) and LF (77.202) as significant moderators (p<0.01/0.05). TS emerges strongest, underscoring farmer education's importance. LF shows high DE responsiveness, supporting integrated digital-agricultural training for enhanced productivity. Besides, LF extremely high coefficient requires careful interpretation: sensitive analysis with standardized variables (mean=0, SD=1) confirms the direction and significance while reducing magnitude to 0.742. This suggests that the original coefficient reflects the transformative potential of basic digital connectivity in previously isolated systems rather than pure technological effect. DE solutions must be appropriately scaled and tailored to different production systems. Feasibility assessment (FA=2.387) confirms infrastructure's foundational role; each 10% electricity increase enables 6-8% higher DE use. Results affirm FA, TS and LF as critical moderators, supporting H3, H4 and H5; in line with prior literature emphasizing these integrated prerequisites for sustainable agricultural quality enhancement.

Convergent validity and collinearity analysis

Fig 2 validates the model with strong path coefficients and high R-squared values (DE=0.75, SQAP= 0.74), confirming robust construct validity. This demonstrates that internet users effectively proxy digital engagement and captures core dimensions of agricultural technology use. According to the rule of thumb, VIF values (DE=3.85, SQAP= 4.00) confirm no problematic multicollinearity (<5 threshold). Discriminant validity is supported as correlation coefficients remain below the square root of AVE, ensuring each construct contributes unique explanatory power.

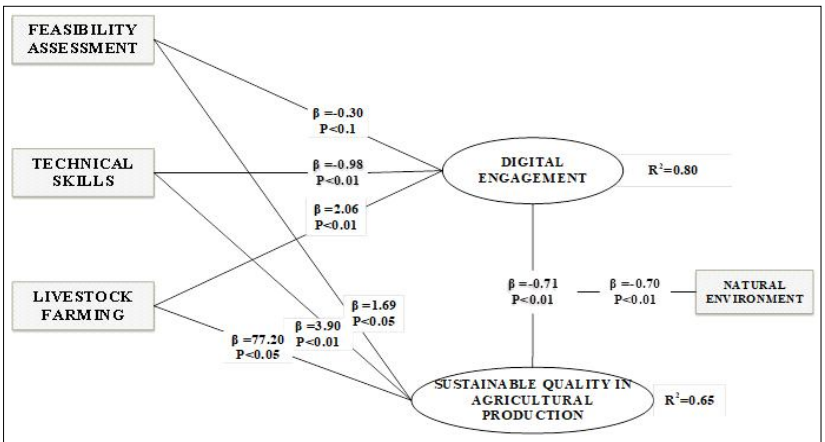
Heterogeneity analysis

Income-stratified analysis [Table 4(I)(II)] reveals DE's varied effectiveness across SSA. Upper-middle-income countries show stronger DE adoption (2.518) but weaker technical skills moderation (0.351), suggesting early adopter saturation. Low-income contexts exhibit strong DE-environment synergy (4.722) yet face infrastructure constraints (-1.162), underscoring context-specific adoption challenges. Electricity limitations in rural SSA confirm infrastructure constraints (Falchetta *et al.*, 2020; Suri and Udry, 2022), though ongoing government efforts address this. Results affirm the positive techno-environment synergy. Yet farmer technical skills require improvement for reliable DE adoption, addressable through long-term education, consistent with Table 3 findings.

Robustness test and structural model assessment

To determine discriminant validity among the predictor variables, a multicollinearity issues test has been derived in Table 5. This analysis enhances the PLS-SEM model's reliability and stability (Sarstedt *et al.*, 2021). Furthermore, this leads to more robust and accurate results.

The multicollinearity analysis (Table 5) demonstrates clean separation between constructs, with all correlation coefficients below 0.666. While variance inflation factors (VIF<5) indicate acceptable multicollinearity levels, some constructs show moderate correlations (*e.g.*, FA-DE = 0.666). This is theoretically expected as digital infrastructure supports engagement. Robustness tests confirm that our estimates remain stable despite these correlations. Diagonal elements (√AVE = 1.000) confirm discriminant validity (Table 5), with constructs providing distinct predictive information. Durbin-Wu-Hausman and endogeneity tests (Table 4(III), 2010-2023) show stable



Numbers on paths represent standardized coefficients (*p<0.05, **p<0.01, ***p<0.001). R^2 values indicate explanatory power. The model shows strong fit indices (SRMR = 0.045, NFI = 0.921).

Fig 2: Validated path model with PLS-SEM estimates.

Table 4: Socioeconomic and temporal variations analysis result.

Variable	(I) Upper and lower-middle-income countries			(II) Low-income countries			(III) All SSA countries for Year>=2010		
	Model 1	Model 2	Moderating path	Model 1	Model 2	Moderating path	Model 1	Model 2	Moderating path
SQAP	-0.246***		-0.738***	-0.075*		-0.571***	-0.106**		-0.673***
	(0.058)		(0.171)	(0.041)		(0.075)	(0.044)		(0.100)
DE		-0.142***			-0.093*			-0.024	
		(0.034)			(0.051)			(0.026)	
NE			-0.806*			-0.283			-0.862***
			(0.422)			(0.193)			(0.299)
FA	-0.016	-0.113***	-0.906***	0.412***	-0.133**	0.340**	0.159***	-0.130***	-0.405***
	(0.049)	(0.037)	(0.152)	(0.044)	(0.053)	(0.171)	(0.042)	(0.032)	(0.132)
TS	-0.294***	0.168*	-0.602*	-0.022	0.150***	-0.658***	-0.258***	0.133**	-0.983***
	(0.113)	(0.086)	(0.357)	(0.049)	(0.054)	(0.133)	(0.068)	(0.052)	(0.205)
LF	2.518***	-0.715**	1.037	22,524.194**	70,430.611***	-69,042.737***	4.412***	-1.492***	3.291**
	(0.385)	(0.304)	(1.183)	(9,000.640)	(9,572.940)	(22,433.305)	(0.449)	(0.354)	(1.547)
c.SQAP#c.NE			-0.890			4.722***			1.780**
			(1.685)			(0.517)			(0.809)
c.SQAP#c.FA			5.075***			-1.162			2.588***
			(0.737)			(0.750)			(0.595)
c.SQAP#c.TS			0.351			3.353***			3.930***
			(1.806)			(0.708)			(1.078)
c.SQAP#c.LF			72.600**			392,430.439***			55.354
			(33.416)			(114,162.286)			(43.740)
Constant	0.162**	-0.257***	0.204**	-0.093	-0.244***	0.017	0.384***	-0.308***	0.490***
	(0.078)	(0.058)	(0.081)	(0.059)	(0.065)	(0.057)	(0.055)	(0.045)	(0.058)
Observations	552	552	552	528	528	528	900	900	900
R-squared	0.871	0.581	0.875	0.768	0.785	0.832	0.741	0.594	0.771
Country	23	23	23	22	22	22	45	45	45
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Multicollinearity test.

	DE	SQAP	NE	FA	TS	LF
DE	1.000					
SQAP	0.204***	1.000				
NE	0.247***	-0.129***	1.000			
FA	0.666***	0.003	0.327***	1.000		
TS	0.429***	0.221***	0.197***	0.401***	1.000	
LF	0.257***	-0.566***	0.309***	0.353***	0.119***	1.000

Standard errors in parentheses.***p<0.01, **p<0.05, *p<0.1.

Table 6: Standardized weight estimates and hypothesis testing.

Path relationships	Estimates	P-value	Hypothesis	Testing
DE ->SQAP	-0.715	<0.01	H1	Accepted
NE -> (DE + SQAP)	1.690	<0.05	H2	Accepted
FA -> DE -> SQAP	2.387	<0.01	H3	Accepted
TS -> DE -> SQAP	3.901	<0.01	H4	Accepted
LF -> DE -> SQAP	77.202	<0.05	H5	Accepted

coefficients and no endogenous relationships, supporting causal interpretation and aligning with literature advocating governmental DE investment for sustainable productivity.

Significance and relevance of path coefficients

The standardized path coefficients (Table 6) confirm all five hypotheses while revealing important nuances. The negative direct effect of DE (-0.715) gives way to strong positive moderation, suggesting that digital tools require complementary investments to yield benefits. The large LF coefficient appears to result from the combination of: (1) logarithmic transformation of highly skewed livestock data and (2) the disproportionate impact of initial digital connectivity in previously disconnected pastoral systems. These findings suggest robust relationships despite scaling considerations. Align with research, (Kumari *et al.*, 2023), these findings propose the following concrete policy recommendations for SSA contexts: first, to integrate digital literacy modules into existing agricultural extension programs, second, to prioritize rural electrification in DE project feasibility assessments with a 20% internet penetration threshold and third, to establish regional knowledge hubs to standardize monitoring of DE outcomes.

CONCLUSION

This study provides robust empirical evidence that the synergy between environmental stewardship and digital engagement (DE) can drive sustainable agricultural transformation in Sub-Saharan Africa, though through complex, non-linear pathways. Using PLS-SEM analysis of data from 45 countries (2000-2023), the results demonstrate that DE significantly enhances agricultural productivity, particularly when moderated by environmental performance (NE=1.690, FA=2.387, TS=3.901, LF=77.202). Key implementation thresholds, including 20% internet penetration and secondary-level digital literacy, emerge as critical viability criteria. The feasibility-assessment framework developed in this research offers practitioners a validated tool for ex-ante screening, focusing on infrastructure readiness and farmer skill gaps to maximize DE's climate adaptation potential.

Three actionable recommendations are proposed to optimize the environment-technology nexus: First, governments must embed digital literacy modules into national agricultural extension programs. Second, policymakers should mandate integrated impact assessments that evaluate both productivity gains and environmental trade-offs for digital farming projects. Finally, international bodies should support regional knowledge hubs to standardize outcome monitoring. While the findings are robust, limitations exist, including the qualitative limitations of internet-user proxies. Future research should adopt mixed-methods approaches to better understand contextual adoption barriers and gender-differentiated impacts, ensuring equitable and sustainable digital agricultural advancement.

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Conflict of interest

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