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Human-AI Hybrid Workplace Optimization and Productivity in Labor-Intensive Agricultural Operations in Centre Region of Cameroon: An Empirical Study

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Abstract

Background: Agriculture in Cameroon's Centre Region faces labor shortages and stagnating productivity, with a 15% decline in the agricultural workforce over five years and annual productivity growth of only 1.5%, while evidence on human-AI collaboration in Central African agriculture remains scarce.
Objective: This study examined the effect of human-AI collaboration intensity on operational productivity and the influence of hybrid workplace optimization on workforce outcomes in labor-intensive agricultural operations.
Method: A cross-sectional survey was conducted among 138 agricultural operators selected through stratified random sampling from enterprises and cooperatives in Mfoundi, Méfou-et-Afamba, and Lekié. Data from a validated questionnaire were analyzed using Pearson correlation and multiple regression.
Results: All five collaboration dimensions were positively correlated with productivity, with AI-human task sharing showing the strongest association ($r = 0.485$, $p < 0.001$). Hybrid workplace optimization explained 37.9% of the variance in workforce outcomes ($R^2 = 0.379$, $p < 0.001$), and training and skill development was the strongest predictor ($\beta = 0.242$, $p = 0.003$).
Conclusion: Productivity gains from AI in resource-constrained agriculture depend on how deliberately human-AI collaboration is organized rather than on technology deployment alone. Agri-businesses, cooperatives, and extension services should prioritize training, organizational support, and clear role definition, while longitudinal research is needed to confirm causality.

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INTRODUCTION

The agricultural sector in Sub-Saharan Africa confronts an unprecedented convergence of challenges that threaten food security, rural livelihoods, and economic development. Agricultural productivity in Sub-Saharan Africa has grown at only 1.8% annually over the past decade, compared to 3.5% in Southeast Asia and 4.2% in South America, while evidence on the digital technologies smallholder food producers actually use to close this gap remains limited (Choruma et al., 2024).

The International Labour Organization ILO, (2017) reports that the agricultural workforce in Central Africa has declined by approximately 18% since 2015, with the average age of farmers exceeding 55 years a trend driven by rural-to-urban migration, limited youth engagement in agriculture, and the increasing vulnerability of farming to climate shocks. In Cameroon, agriculture employs approximately 70% of the labor force and contributes 22% to the national GDP, yet productivity growth has stagnated at 1.5% annually.

These challenges are particularly acute in Cameroon's Centre Region, the country's primary food production zone, where smallholder farmers constitute approximately 75% of agricultural producers and face intensifying pressures from climate variability, soil degradation, and labor shortages (Chimi et al., 2024). The Centre Region of Cameroon, encompassing the departments of Mfoundi, Méfou-et-Afamba, and Lekié, represents a microcosm of the broader challenges facing Central African agriculture.

This region produces approximately 40% of Cameroon's food crops, including cassava, maize, plantain, yams, and vegetables (Chimi et al., 2024). However, the region's agricultural workforce has declined by 15% over the past five years, with young people increasingly migrating to Yaoundé and Douala for urban employment (Marie et al., 2023). The combination of declining workforce availability, climate variability, and limited access to modern agricultural technologies has created urgent pressure to enhance productivity through innovative solutions. Artificial intelligence has emerged as a transformative force capable of addressing these challenges through capabilities in data analysis, prediction, and automation.

Research from 2021 to 2024 demonstrates a maturation characterized by the transition from experimental proofs-of-concept to field-validated applications exhibiting robust performance and measurable resource efficiency gains in precision management, robotics, and predictive analytics (P. Wu & Zhong, 2025). However, the translation of this technical promise into equitable, scalable, and sustainable agricultural systems in Central Africa is increasingly bottlenecked by critical socio-technical challenges rather than technological limitations including limited digital infrastructure, unreliable electricity access, low digital literacy, and the need for AI systems that account for local agricultural knowledge and practices.

The integration of AI into agricultural operations in Cameroon requires not only technical infrastructure but also workforce adaptation, organizational change, and careful attention to human factors such as trust, training, and task design within contexts of resource constraints. The concept of the human-AI hybrid workplace has gained prominence as organizations recognize that the most powerful combination is actually humans and AI working together, with AI amplifying human expertise rather than replacing it.

In labor-intensive agricultural operations in Cameroon, AI can automate repetitive data tasks such as weather monitoring, pest detection, and yield prediction while humans focus on high-value activities requiring intuition, lived experience, and complex decision-making informed by local knowledge of soils, microclimates, and traditional farming practices (Fügener et al., 2026). Yet, optimizing this hybrid workplace in the Cameroonian context requires understanding how collaboration dynamics influence productivity outcomes a relationship that remains undertheorized and understudied, particularly in Central African agricultural settings where digital transformation faces unique barriers and opportunities.

The human-AI hybrid workplace refers to work environments where human expertise and artificial intelligence systems collaboratively perform tasks, with each complementing the other's capabilities. According to research on human-in-the-loop approaches to applying large language models for farm management, a human-in-the-loop workflow enables the scalable synthesis of agricultural knowledge while maintaining quality control through expert oversight (Mourtzinis et al., 2025). The hybrid workplace concept extends beyond simple automation to encompass interdependent work arrangements where AI handles repetitive, data-intensive tasks while humans provide contextual judgment, intuition, and strategic oversight.

As shown by Fügener et al., (2026), AI delivers the greatest benefit when it augments rather than substitutes for human judgement, amplifying what experts already know rather than replacing the need to think. In the Cameroonian agricultural context, this conceptualization takes on particular significance, as AI systems must be designed to complement not only formal agricultural knowledge but also traditional farming practices and local ecological knowledge that have been developed over generations.

The optimal configuration of human-AI collaboration varies across tasks, contexts, and organizational capabilities, and in Cameroon, this variation is influenced by factors such as digital infrastructure availability, electricity access, internet connectivity, and the educational background of agricultural workers. Human-AI collaboration intensity refers to the frequency, depth, and integration level of interactions between human workers and AI systems in performing operational tasks. Research on agricultural digital twins and human-AI collaboration represents an emerging meta-layer that synthesizes data streams into high-fidelity simulations and decision environments, enabling farmers and agronomists to test management strategies before implementation (P. Wu & Zhong, 2025).

Collaboration intensity exists on a spectrum from occasional AI-assisted decision-making to deeply integrated, real-time human-AI teamwork where AI continuously learns from human feedback and adapts recommendations accordingly. In the Cameroonian context, collaboration intensity is particularly influenced by the reliability of digital infrastructure and the availability of AI tools designed for local agricultural conditions. Operational productivity in agriculture refers to the efficiency with which inputs are converted into outputs, encompassing labor productivity, resource utilization, and output per unit of input.

Studies examining AI's role in shaping agricultural workforce management have found that AI significantly reduces manual labor in repetitive tasks, allowing firms to reallocate human resources to higher-value roles (Qorri et al., 2024). Operational productivity is not merely output quantity but also quality, timeliness, and sustainability of agricultural operations dimensions that are particularly salient in Cameroonian agricultural contexts where post-harvest losses due to poor storage and transportation infrastructure can reach 30-40% of production, and where timing of planting and harvest significantly influences market prices and food security.

Workforce outcomes encompass the effects of workplace changes on employees' performance, satisfaction, and well-being. In the context of human-AI hybrid workplaces, workforce outcomes include workforce efficiency, job satisfaction, employee engagement, reduced physical strain, and skill development opportunities. Research on AI adoption in agri-tech firms has found that successful AI implementation requires attention to workforce outcomes, as employee resistance and dissatisfaction can undermine technological investments (Qorri et al., 2024).

In the Cameroonian agricultural context, workforce outcomes take on additional significance given the challenges of rural-urban migration, aging farming populations, and the need to attract young people to agriculture. Positive workforce outcomes particularly skill development and reduced physical drudgery are essential for making agriculture an attractive career option for Cameroon's youth. This study is grounded in three complementary theoretical frameworks that explain the mechanisms through which human-AI hybrid workplace optimization influences productivity. The Socio-Technical Systems Theory, as articulated by Kudina & van de Poel, (2024), emphasizes the interdependence of social and technical systems within organizations.

The theory posits that optimal organizational performance requires joint optimization of both social (people, skills, culture, work relationships) and technical (tools, technologies, processes) subsystems. Research has argued that the next frontier of innovation in agricultural AI lies not in isolated algorithms but in integrated socio-technical systems where technical capabilities and human factors are jointly designed and optimized (P. Wu & Zhong, 2025).

This theory explains why human-AI collaboration must account for both technical capabilities and human factors such as trust, training, and organizational culture. The theory suggests that productivity gains from AI adoption depend not only on technical sophistication but also on how well the social system adapts to and integrates with technical changes a dynamic that is particularly salient in contexts where digital infrastructure is limited and traditional farming practices remain central to agricultural production.

The Task-Technology Fit Theory, as synthesized by Jeyaraj, (2022), posits that performance improves when technology characteristics match task requirements. The theory suggests that the impact of technology on individual performance depends on the fit between technology functionality and the tasks users need to perform. This framework is particularly relevant for understanding how AI tools must be designed to fit the specific needs of agricultural tasks and the capabilities of farm workers. Research emphasizes that the effective use of AI in agriculture requires building for the people doing the work, ensuring the tool makes someone's job easier or it won't get used (Fügener et al., 2026).

The Human-in-the-Loop Framework emerges from research on machine learning and AI systems, emphasizing the importance of human oversight in automated decision-making. Studies have developed semi-automated, human-in-the-loop pipelines adhering to systematic review protocols for literature screening, outperforming standalone models (Mourtzinis et al., 2025). The framework recognizes that while AI can process large datasets and identify patterns, human judgment remains essential for interpreting results, making contextual decisions, and handling edge cases. Research by Fügener et al., (2026) modelled how organisations should allocate judgement tasks between people and AI, distinguishing automation, in which AI replaces the worker, from augmentation, in which AI works alongside the worker.

The study found that the optimal configuration depends on the type of human-AI complementarity present: AI is best used to automate comparatively easy tasks, to augment humans on tasks where human and machine performance are similar, and to stay out of the way on the most difficult tasks, which humans should handle alone. This research provides important insights into the organizational prerequisites for successful human-AI collaboration, particularly the importance of deliberate task design and human resource reallocation rather than technology-driven implementation. However, the study relies on analytical modelling validated with experimental image-classification data from a developed economy, limiting the generalizability of findings to Sub-Saharan African agricultural settings where data infrastructure and organizational capabilities differ substantially.

Research on human-in-the-loop approaches to applying large language models for farm management by Mourtzinis et al., (2025) revealed that while LLMs can generate soybean management plans that experts rate favorably, no system was entirely free of negative ratings. The study found that Gemini's plan received the highest overall ratings (79% good or excellent), followed by OpenAI (69%) and the human-in-the-loop system (68%). This research underscores the importance of combining human expertise with AI capabilities to achieve optimal outcomes, but the focus remains on model performance rather than collaboration intensity as a predictor of organizational productivity.

Furthermore, the study was conducted in a developed agricultural context (North America) and did not address the unique challenges of applying AI in Central African agricultural systems where data availability, infrastructure, and expertise differ substantially. Daum, (2025) examined how digitalisation reshapes knowledge and skills in agriculture across five levels: farmers, farms, farm workers, the agricultural value chain, and agricultural knowledge and innovation systems.

The review found that digital tools can either deskill or reskill and upskill the workforce depending on how the technology is designed, what capabilities users already hold, and how much training accompanies the tool, so that successful implementation depends not only on technical capabilities but also on workforce readiness and adaptation. However, the study did not systematically examine how collaboration intensity varies across organizations or

how such variation influences productivity outcomes, and its evidence base is drawn largely from contexts that differ substantially from Central African conditions.

The study highlighted that the combination of intuition and lived experience cannot be duplicated with technology in the near term. This perspective emphasizes that technology should guide humans and amplify their strengths rather than replace them, suggesting that hybrid workplace optimization requires attention to how AI tools support rather than supplant human judgment. However, this research is based on conceptual arguments rather than empirical data and does not address the specific challenges of implementing hybrid workplace optimization in resource-constrained agricultural contexts.

Studies on human resource management and labour-saving technology in agriculture by Qorri et al., (2024) found that the adoption of such technologies, including artificial intelligence, depends on a small set of HRM functions: knowledge management, change management, labour allocation, sustainability allocation, and regulatory compliance. Firms that manage these functions deliberately are better able to absorb new technology, whereas those that treat adoption as a purely technical exercise encounter resistance and underused tools.

This research demonstrates that effective hybrid workplace optimization requires systematic attention to workforce transitions, including change management, training, and job redesign. However, the study relies on an integrative review and science mapping of the existing literature rather than primary quantitative analysis of workforce outcome predictors, and the corpus it synthesises is dominated by European and North American agricultural contexts that differ substantially from Central African settings.

Comparing these empirical studies reveals several limitations and gaps that this research addresses. First, studies by Fügener et al., (2026); Nguyen & Elbanna, (2025) rely primarily on analytical modelling, conceptual argument, or review-based evidence drawn from developed economies rather than systematic empirical research with rigorous sampling and statistical analysis applicable to African settings. While these sources provide valuable insights, they do not offer generalizable evidence on the relationship between collaboration intensity and productivity in Sub-Saharan African agricultural contexts characterized by different infrastructure, workforce characteristics, and organizational dynamics.

Second, studies by Mourtzinis et al., (2025); Wu & Zhong, (2025) focus on technical performance of AI systems rather than organizational productivity outcomes, leaving the translation from technical capability to operational impact underexamined, particularly in contexts where digital infrastructure and technical support are limited. Third, Daum, (2025); Qorri et al., (2024) examine workforce adaptation but do not systematically quantify how hybrid workplace optimization dimensions predict workforce outcomes, and their research focuses on developed country contexts rather than the challenges facing Central African agriculture.

Despite growing recognition of AI's potential in agriculture, limited empirical research has systematically examined how human-AI collaboration dynamics specifically influence productivity in labor-intensive agricultural settings in Sub-Saharan Africa, where most available studies remain short-term and pilot-based (Shitaye et al., 2026). Several studies have explored AI's role in optimizing business processes and enhancing human capital productivity in developed economies (Daum, 2025), while others have examined human-in-the-loop approaches to farm management primarily in North American and European contexts (Mourtzinis et al., 2025).

However, these studies have not quantified collaboration intensity as a distinct predictor of productivity outcomes in African agricultural systems, where contextual factors such as limited digital infrastructure, varying literacy levels, and the importance of traditional agricultural knowledge create unique dynamics for human-AI collaboration. Furthermore, research on workforce adaptation to AI has emphasized the importance of training and job restructuring (Qorri et al., 2024), yet the relationship between hybrid

workplace optimization dimensions and workforce efficiency remains underexplored in developing country contexts.

Critically, existing empirical studies have predominantly focused on developed agricultural systems in North America, Europe, and increasingly Southeast Asia, leaving a significant gap in understanding how human-AI collaboration functions in labor-intensive agricultural contexts in Central Africa, where resource constraints, infrastructure limitations, and workforce characteristics differ substantially, although recent West African evidence indicates that extension agents' engagement with generative AI tools is associated with measurable changes in advisory performance (Gouroubera et al., 2026).

Despite growing evidence supporting human-AI collaboration in agriculture, significant gaps remain in understanding how hybrid workplace optimization specifically influences productivity in labor-intensive agricultural operations in Central Africa. No studies quantify collaboration intensity as a distinct predictor of productivity in African agriculture, research on hybrid workplace optimization dimensions predicting workforce outcomes in Central Africa remains limited, and existing studies focus on developed economies or technical performance rather than organizational outcomes in resource-constrained settings.

This study addresses these gaps by making several novel contributions to the literature. First, whereas previous research has examined AI adoption as a binary variable (adopted versus not adopted), this study operationalizes human-AI collaboration intensity as a multidimensional construct encompassing frequency of AI-assisted decision-making, depth of AI integration, level of task sharing, real-time feedback utilization, and problem-solving frequency. This nuanced conceptualization allows for more precise understanding of how varying levels of collaboration influence productivity outcomes.

Second, this study provides empirical evidence from a Central African country context Cameroon's Centre Region where workforce challenges, technological adaptation dynamics, and infrastructural constraints differ substantially from those in developed agricultural systems. Third, this research integrates three theoretical frameworks Socio-Technical Systems Theory, Task-Technology Fit Theory, and the Human-in-the-Loop Framework to interpret findings and extend theoretical understanding of human-AI collaboration in agricultural contexts characterized by resource constraints and unique socio-cultural factors.

The theoretical contribution of this study lies in extending Socio-Technical Systems Theory to the specific context of human-AI collaboration in Central African agriculture. While the socio-technical extension by Herrmann & Pfeiffer, (2023) emphasized the interdependence of social and technical systems in industrial contexts, this study demonstrates that similar dynamics operate in agricultural settings where AI systems interact with human workers, but with unique adaptations required for contexts characterized by limited infrastructure, varying digital literacy, and the importance of traditional agricultural knowledge.

The study contributes to Task-Technology Fit Theory by identifying specific characteristics of agricultural tasks in Cameroon (e.g., weather-dependent decisions, crop-specific knowledge, seasonal timing, and the integration of traditional farming practices) that influence the effectiveness of AI collaboration. Furthermore, the study extends the Human-in-the-Loop Framework by demonstrating that collaboration intensity not merely the presence or absence of human oversight significantly predicts productivity outcomes, even in resource-constrained settings.

The specific objectives of this study are to assess the effect of human-AI collaboration intensity on operational productivity in labor-intensive agricultural operations in Cameroon's Centre Region and to examine the influence of human-AI hybrid workplace optimization on workforce efficiency and job satisfaction among Cameroonian agricultural workers. The following hypotheses guide this study: human-AI collaboration intensity has a significant positive influence on operational productivity in labor-intensive agricultural operations in Cameroon's Centre Region (H_1), and human-AI hybrid workplace optimization

has a significant positive influence on workforce efficiency and job satisfaction among agricultural workers in Cameroon's Centre Region (H_2).

This study contributes to both academic knowledge and practical application by providing empirical evidence on the relationship between human-AI hybrid workplace configurations and productivity outcomes in labor-intensive agriculture in Central Africa, while offering actionable insights for Cameroonian agri-business managers, agricultural cooperatives, extension services, policymakers, and technology providers seeking to optimize human-AI collaboration in contexts of resource constraints and unique socio-cultural dynamics.

RESEARCH METHOD

Research Design and Setting

This study employed a quantitative, cross-sectional survey design to examine the relationship between human-AI hybrid workplace optimization and productivity in labor-intensive agricultural operations in Cameroon's Centre Region. A cross-sectional design was appropriate because the research objectives focus on establishing relationships between variables at a single point in time rather than tracking changes over time (Creswell & Creswell, 2017); consequently, the findings are interpreted as associations rather than causal effects.

The study was conducted in three departments of the Centre Region: Mfoundi, which includes the capital city Yaoundé and its surrounding agricultural areas; Méfou-et-Afamba, an important food production zone; and Lekié, which is known for intensive cassava and maize cultivation. Together, these departments form the primary food production zone of the region, dominated by cassava, maize, plantain, and vegetable cultivation. Data were collected between January and March 2026, coinciding with the main dry-season agricultural activities.

Population, Sample, and Sampling Technique

The study population comprised agricultural operators, namely farm managers, agri-business owners, cooperative leaders, and operations supervisors, in agricultural enterprises and cooperatives in the Centre Region that had implemented AI-based decision support tools, defined as mobile applications or computer-based systems that provide recommendations on planting, pest management, irrigation, or marketing. Respondents were eligible if they were employed in, or were members of, a registered agricultural enterprise or cooperative; had direct responsibility for, or regular involvement in, operational decision-making; had used AI-based decision support tools for at least one year; and were willing and able to provide informed consent.

Respondents were selected using stratified random sampling. Strata were defined by enterprise or cooperative size (micro: <10 members; small: 10–49 members; medium: 50–199 members), type of agricultural operation (cassava, maize, plantain, vegetable, and mixed crop systems), and duration of AI adoption (<2 years, 2–5 years, >5 years). Within each stratum, respondents were randomly selected from lists provided by the regional agricultural extension services of the Ministry of Agriculture and Rural Development (MINADER) and from the membership rosters of agricultural cooperatives in the three departments.

An a priori power analysis for multiple regression with five predictors, a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and a statistical power of 0.80 indicated a minimum required sample of approximately 92 respondents (Lakens, 2022). The sample was increased to 150 to accommodate anticipated non-response and incomplete questionnaires, given the transportation and communication constraints of data collection in rural Cameroon. Of the 150 questionnaires distributed, 138 were complete and retained for analysis, yielding a response rate of 92%.

Research Instrument and Measurement

Data were collected using a structured questionnaire prepared in French and English and translated into Ewondo and Bassa where necessary. The questionnaire was administered through face-to-face interviews conducted by trained research assistants and extension officers. It comprised five sections: respondent and enterprise characteristics (gender, age, education, enterprise size, years of AI adoption, primary agricultural activity, access to electricity and internet, and type of mobile phone); human-AI collaboration intensity (15 items); hybrid workplace optimization (15 items); operational productivity (14 items); and workforce outcomes (12 items). All substantive items were measured on a five-point Likert scale.

Human-AI collaboration intensity was operationalized through five dimensions: frequency of AI-assisted decision-making, depth of AI integration in daily operations, level of AI-human task sharing, real-time AI feedback utilization, and AI-assisted problem-solving frequency. Hybrid workplace optimization was measured through five dimensions: clear role definition between humans and AI, training and skill development for AI use, AI tools designed for ease of use, organizational support for AI adoption, and change management and communication.

Operational productivity was measured through five indicators: labor productivity and time efficiency, resource utilization and cost efficiency, output quality and consistency, decision-making speed and accuracy, and overall operational efficiency perception. Workforce outcomes were measured through five indicators: workforce efficiency and productivity, employee job satisfaction, employee engagement and motivation, reduced physical strain and drudgery, and skill development and career growth. Because all measures were self-reported, operational productivity reflects respondents' perceptions rather than objectively recorded output.

Pilot Testing, Validity, and Reliability

The questionnaire was pre-tested with 25 agricultural operators from the target population who were excluded from the final sample. The pilot test assessed the clarity and comprehensibility of items, given varying literacy levels and the need for translation into local languages, identified ambiguous questions, and provided preliminary reliability estimates. Several items were subsequently reworded, the completion time was adjusted to approximately 30–40 minutes to suit the face-to-face interview format, and data collection procedures were refined, including the training of local research assistants in French and the local languages.

Construct validity was assessed through factor analysis using principal component extraction with Varimax rotation. For the human-AI collaboration intensity scale, factor analysis confirmed a five-factor structure accounting for 67.2% of total variance, with factor loadings ranging from 0.59 to 0.88. For the hybrid workplace optimization scale, factor analysis confirmed a five-factor structure accounting for 65.8% of total variance, with factor loadings ranging from 0.56 to 0.86.

For the operational productivity scale, factor analysis confirmed a single-factor structure accounting for 58.4% of total variance, with factor loadings ranging from 0.59 to 0.83. For the workforce outcomes scale, factor analysis confirmed a single-factor structure accounting for 56.1% of total variance, with factor loadings ranging from 0.57 to 0.81. Content validity was established through expert review by three academic researchers with expertise in African agricultural economics, technology adoption, and organizational behavior, as well as two Cameroonian agricultural extension officers with deep knowledge of local farming systems and practices.

The expert review team assessed whether items adequately represented the constructs being measured in the Cameroonian agricultural context. All five experts rated the questionnaire as having adequate content validity (content validity ratio $= 0.76$, exceeding

the minimum of 0.58 for five experts). Reliability was assessed using Cronbach's alpha coefficients. The overall questionnaire demonstrated excellent reliability ($\alpha = 0.88$).

The human-AI collaboration intensity scale showed good reliability ($\alpha = 0.85$, with subscale α ranging from 0.77 to 0.83). The hybrid workplace optimization scale showed good reliability ($\alpha = 0.83$, with subscale α ranging from 0.74 to 0.81). The operational productivity scale showed acceptable reliability ($\alpha = 0.81$), and the workforce outcomes scale showed acceptable reliability ($\alpha = 0.79$). These coefficients exceed the recommended threshold of 0.70 for acceptable reliability (Hair & Alamer, 2022).

Ethical Considerations

The study received ethical approval from an institutional review board (IRB) prior to data collection. Written informed consent was obtained from literate participants before questionnaire administration. Because the study involved minimal risk and did not collect sensitive personal information, the IRB approved a waiver of documented consent signature for participants with limited literacy; for these participants, the information sheet was read aloud in the presence of a witness, and verbal consent was recorded by the research assistant. Questionnaires were anonymized using identification codes, and data were stored on password-protected computers accessible only to the research team.

Data Analysis

Data were analyzed using descriptive and inferential statistics in SPSS version 27.0. Frequencies and percentages were used to summarize respondent characteristics, while means and standard deviations were used to summarize responses to the scale items. Composite scores for each dimension and construct were computed by averaging the corresponding items and were interpreted on the five-point scale (1 = very low, 3 = moderate, 5 = very high).

Before the regression analysis, four assumptions were examined. Normality of residuals was assessed using the Shapiro-Wilk test together with skewness and kurtosis values, with acceptable ranges of -2 to $+2$ and -7 to $+7$, respectively (Aryadoust & Jia, 2026). Multicollinearity was assessed using variance inflation factors (VIF), with values below 5 indicating no serious concern (Hair & Alamer, 2022). Heteroscedasticity was assessed using the Breusch-Pagan test, with $p > 0.05$ indicating constant error variance, and linearity was evaluated through scatterplots of residuals against predicted values.

Hypothesis H_1 was tested using Pearson correlation analysis between each of the five collaboration intensity dimensions and the composite operational productivity score, with r^2 reported as the proportion of shared variance. Hypothesis H_2 was tested using multiple linear regression, in which the five hybrid workplace optimization dimensions were entered simultaneously as predictors of the composite workforce outcome score. Model fit was evaluated using R^2, adjusted R^2, and the F-test; overall effect size was expressed as Cohen's f^2; and the relative contribution of each predictor was assessed using standardized coefficients (β), semi-partial correlations, and the incremental variance explained when each predictor was entered last (ΔR^2). Statistical significance was set at $p < 0.05$ (two-tailed).

RESULT AND DISCUSSION

Assumption Testing Results

Prior to conducting regression analysis, assumptions were tested and all were satisfactorily met:

1. Normality: The Shapiro-Wilk test for residuals was not significant ($W = 0.986$, $p = 0.218$), indicating that residuals were normally distributed. Skewness (-0.338) and kurtosis (0.259) values were within acceptable ranges.
2. Multicollinearity: Variance inflation factors for all predictor variables ranged from 1.22 to 2.84, well below the threshold of 5, indicating no serious multicollinearity concerns.

3. Heteroscedasticity: The Breusch-Pagan test was not significant ($\chi^2 = 8.12$, df = 5, p = 0.142), indicating constant error variance.
4. Linearity: Scatterplots of residuals versus predicted values showed random distribution, supporting the linearity assumption.

Demographic Characteristics of Respondents

A total of 138 valid questionnaires were returned from 150 distributed, yielding a response rate of 92%. The 12 incomplete questionnaires were excluded due to missing data on key variables (more than 20% of items incomplete).

Table 1. Demographic Characteristics of Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	79	57.2
	Female	59	42.8
Age Group	21-30 years	24	17.4
	31-40 years	38	27.5
	41-50 years	34	24.6
	51-60 years	28	20.3
	Over 60 years	14	10.1
Education Level	No formal education	12	8.7
	Primary school	28	20.3
	Secondary school	35	25.4
	Vocational training	30	21.7
	University degree	33	23.9
Enterprise/Cooperative Size	Micro (<10 members)	48	34.8
	Small (10-49 members)	60	43.5
	Medium (50-199 members)	30	21.7
Years of AI Adoption	< 2 years	44	31.9
	2-5 years	52	37.7
	> 5 years	42	30.4
Primary Agricultural Activity	Cassava production	45	32.6
	Maize cultivation	30	21.7
	Plantain farming	24	17.4
	Vegetable production	22	15.9
	Mixed crop systems	17	12.3
Access to Electricity	Reliable electricity	82	59.4
	Unreliable/no electricity	56	40.6
Internet Connectivity	Regular internet access	72	52.2
	Limited/no internet	66	47.8
Mobile Phone Ownership	Smartphone	98	71.0
	Basic phone	40	29.0

The demographic profile reveals that the majority of respondents were male (57.2%), aged 31-50 years (52.1%), with secondary education or higher (71.0%). Small cooperatives and enterprises (10-49 members) were most represented (43.5%), and cassava production was the primary agricultural activity for 32.6% of respondents. Most respondents had 2-5 years of AI adoption experience (37.7%), with substantial representation across all adoption categories.

Notably, access to infrastructure varied considerably: 40.6% reported unreliable or no electricity access, 47.8% reported limited or no internet connectivity, and 29.0% used only basic mobile phones rather than smartphones. These infrastructural characteristics are important contextual factors that influence the feasibility and effectiveness of human-AI collaboration in the Cameroonian context.

Analysis Based on Objective One: Human-AI Collaboration Intensity and Operational Productivity

Table 2. Descriptive Statistics for Human-AI Collaboration and Operational Productivity

Variable	Mean	SD
Human-AI Collaboration Intensity		
Frequency of AI-assisted decision-making	3.45	1.04
Depth of AI integration in daily operations	3.38	1.01
Level of AI-human task sharing	3.52	0.97
Real-time AI feedback utilization	3.30	1.06
AI-assisted problem-solving frequency	3.58	0.93
Overall Collaboration Intensity	**3.45**	**0.90**
Operational Productivity Indicators		
Labor productivity and time efficiency	3.68	0.90
Resource utilization and cost efficiency	3.61	0.94
Output quality and consistency	3.54	0.96
Decision-making speed and accuracy	3.67	0.88
Overall operational efficiency perception	3.65	0.87
Overall Operational Productivity	**3.63**	**0.82**

Scale: 1 = Very low, 2 = Low, 3 = Moderate, 4 = High, 5 = Very high

The results presented in Table 2 indicate that human-AI collaboration intensity was generally moderate (overall M = 3.45, SD = 0.90), with AI-assisted problem-solving frequency showing the highest mean score (M = 3.58, SD = 0.93) and real-time AI feedback utilization showing the lowest (M = 3.30, SD = 1.06). These moderate levels are consistent with the infrastructural profile of the sample, in which 40.6% of respondents reported unreliable or no electricity and 47.8% reported limited or no internet connectivity, conditions that are likely to restrict continuous and real-time use of AI tools.

Operational productivity indicators were moderate to high (overall M = 3.63, SD = 0.82), with labor productivity showing the highest mean score (M = 3.68, SD = 0.90) and output quality and consistency showing the lowest (M = 3.54, SD = 0.96). The overall operational productivity score of 3.63 indicates that respondents generally perceived their operations as moderately productive a level that reflects both the benefits of AI tools and the ongoing challenges of infrastructure limitations and climate variability in the Centre Region.

Table 3. Relationship between Human-AI Collaboration Intensity and Operational Productivity

Collaboration Dimension	r	p-value	Effect Size (r^2)
Frequency of AI-assisted decision-making	0.428**	<0.001	0.183
Depth of AI integration in daily operations	0.452**	<0.001	0.204
Level of AI-human task sharing	0.485**	<0.001	0.235
Real-time AI feedback utilization	0.406**	<0.001	0.165
AI-assisted problem-solving frequency	0.462**	<0.001	0.213

*Note: *Correlation is significant at $p < 0.01$ level. Effect size r^2 represents proportion of variance explained.*

The Pearson correlation analysis revealed significant positive correlations of moderate magnitude ($r = 0.406–0.485$) between all human-AI collaboration intensity dimensions and operational productivity. The level of AI-human task sharing showed the strongest correlation ($r = 0.485$, $p < 0.001$), sharing 23.5% of the variance with operational productivity. This was followed by AI-assisted problem-solving frequency ($r = 0.462$, $p < 0.001$, $r^2 = 0.213$) and depth of AI integration in daily operations ($r = 0.452$, $p < 0.001$, $r^2 = 0.204$), whereas real-time AI feedback utilization showed the weakest, though still significant, correlation ($r = 0.406$, $p < 0.001$, $r^2 = 0.165$).

These findings support Hypothesis H_1, which posited a significant positive relationship between human-AI collaboration intensity and operational productivity in Cameroonian agricultural operations. All dimensions of collaboration intensity were positively associated with productivity, with task sharing and problem-solving frequency showing the strongest relationships. Because the analysis is correlational, these results indicate association rather than causation; it is also plausible that more productive operations are better positioned to use AI more intensively.

The practical significance of these correlations is noteworthy. The effect sizes (r^2) indicate that the collaboration intensity dimensions share between 16.5% and 23.5% of their variance with operational productivity, suggesting that collaboration intensity is a meaningful correlate of productivity even in resource-constrained settings. For example, the r^2 of 0.235 for AI-human task sharing indicates that nearly one-quarter of the variation in operational productivity is associated with the level of task sharing between humans and AI systems, a practically relevant effect in Cameroonian agricultural operations, where small productivity improvements translate into meaningful food security and economic outcomes for farming families.

Analysis Based on Objective Two: Hybrid Workplace Optimization and Workforce Outcomes

Table 4. Descriptive Statistics for Hybrid Workplace Optimization and Workforce Outcomes

Variable	Mean	SD
Hybrid Workplace Optimization		
Clear role definition between humans and AI	3.54	0.96
Training and skill development for AI use	3.48	1.00
AI tools designed for ease of use	3.42	1.04
Organizational support for AI adoption	3.58	0.93
Change management and communication	3.40	1.01
Overall Hybrid Workplace Optimization	**3.48**	**0.88**
Workforce Outcomes		
Workforce efficiency and productivity	3.64	0.88
Employee job satisfaction	3.58	0.92
Employee engagement and motivation	3.50	0.96
Reduced physical strain and drudgery	3.54	0.94
Skill development and career growth	3.42	1.00
Overall Workforce Outcome	**3.54**	**0.84**

Scale: 1 = Very low/Strongly disagree, 2 = Low/Disagree, 3 = Moderate/Neutral, 4 = High/Agree, 5 = Very high/Strongly agree

Table 4 shows that hybrid workplace optimization characteristics were moderate (overall $M = 3.48$, $SD = 0.88$), with organizational support for AI adoption receiving the highest mean score ($M = 3.58$, $SD = 0.93$) and change management and communication receiving the lowest ($M = 3.40$, $SD = 1.01$). These scores reflect the mixed experiences of

Cameroonian agricultural workers with AI adoption while many organizations provide support, change management and communication remain challenges, particularly given the limited resources available for comprehensive training and communication programs in many cooperatives and agricultural enterprises.

Workforce outcomes were generally moderate to high (overall M = 3.54, SD = 0.84), with workforce efficiency showing the highest mean score (M = 3.64, SD = 0.88) and skill development and career growth showing the lowest (M = 3.42, SD = 1.00). The overall workforce outcome score of 3.54 indicates that respondents generally perceived their workforce outcomes as moderately positive, though the relatively low score for skill development and career growth suggests that AI adoption in Cameroonian agriculture has not yet fully translated into expanded career opportunities for workers an important consideration for attracting and retaining young people in agriculture.

Table 5. Regression Analysis of Hybrid Workplace Optimization on Workforce Outcomes

Predictor Variable	β	t	p-value	Semi-partial r	ΔR^2
Clear role definition between humans and AI	0.198*	2.41	0.017	0.184	0.034
Training and skill development for AI use	0.242**	2.98	0.003	0.221	0.050
AI tools designed for ease of use	0.175*	2.14	0.034	0.163	0.027
Organizational support for AI adoption	0.212*	2.63	0.009	0.196	0.039
Change management and communication	0.189*	2.30	0.022	0.173	0.030

*Note: $R^2 = 0.379$, Adjusted $R^2 = 0.360$, $F(5, 132) = 15.42$, $p < 0.001$. *$p < 0.05$, *$p < 0.01$. *ΔR^2 represents incremental variance explained by each predictor when entered last.*

The multiple regression analysis revealed that hybrid workplace optimization significantly predicted workforce outcomes, $F(5, 132) = 15.42$, $p < 0.001$, accounting for 37.9% of the variance in workforce outcomes ($R^2 = 0.379$). The adjusted R^2 of 0.360 indicates that after accounting for the number of predictors, the model still explains over 36% of the variance a large effect size according to Emerson, (2023) conventions ($f^2 = 0.61$).

Training and skill development for AI use emerged as the strongest predictor ($\beta = 0.242$, $p = 0.003$), uniquely explaining 5.0% of variance when entered last. This was followed by organizational support for AI adoption ($\beta = 0.212$, $p = 0.009$, $\Delta R^2 = 0.039$) and clear role definition between humans and AI ($\beta = 0.198$, $p = 0.017$, $\Delta R^2 = 0.034$). AI tools designed for ease of use ($\beta = 0.175$, $p = 0.034$, $\Delta R^2 = 0.027$) and change management and communication ($\beta = 0.189$, $p = 0.022$, $\Delta R^2 = 0.030$) also made significant but smaller contributions.

These findings support Hypothesis H_2, which posited that human-AI hybrid workplace optimization has a significant positive influence on workforce efficiency and job satisfaction among Cameroonian agricultural workers. The regression model demonstrates that all five dimensions of hybrid workplace optimization significantly predict workforce outcomes, with training and skill development showing the strongest influence. The large effect size ($R^2 = 0.379$; $f^2 = 0.61$) indicates that hybrid workplace optimization is a practically meaningful predictor of workforce outcomes in Cameroonian agricultural operations.

The relative importance of predictors deserves attention in the Cameroonian context. The finding that training and skill development is the strongest predictor suggests that workforce readiness specifically, the knowledge and skills needed to effectively use AI tools is paramount for achieving positive workforce outcomes.

Given that 40.6% of respondents lacked reliable electricity and 47.8% had limited or no internet access, this finding highlights the importance of developing training programs that work within these infrastructural constraints, such as offline training materials, peer-to-

peer learning networks, and simplified interfaces that work on basic mobile phones. Organizational support and clear role definition also play important roles, suggesting that both structural (role clarity) and cultural (organizational support) factors influence workforce outcomes in the Cameroonian context.

Discussion

Human-AI Collaboration Intensity and Operational Productivity

The findings revealed significant positive relationships between all dimensions of human-AI collaboration intensity and operational productivity, supporting H_1. This pattern is consistent with Fügener et al., (2026), whose analytical model shows that AI generates the greatest value when it augments rather than replaces human judgement, and with Nguyen & Elbanna, (2025), who conceptualize human-AI augmentation as a distinct mode of workplace collaboration. However, whereas these studies relied on analytical modelling, experimental data, or literature synthesis from developed economies, the present study provides survey-based evidence from Central Africa that collaboration intensity, not merely the presence or absence of AI, is associated with productivity even amid infrastructural constraints.

The strongest association was observed between AI-human task sharing and productivity ($r = 0.485$, $r^2 = 0.235$). This suggests that clearly defined collaboration structures, in which tasks are systematically divided according to the comparative strengths of humans and AI, enhance productivity more than simply increasing the frequency of AI use. This interpretation corresponds to the task-allocation logic of Fügener et al., (2026), who recommend using AI to automate comparatively easy tasks, to augment humans where human and machine performance are similar, and to leave the most difficult tasks to humans.

In Cameroon, where digital infrastructure is limited, organizations should therefore prioritize the *quality* of task sharing over the quantity of AI usage. This finding extends Task-Technology Fit Theory (X. Wu & Jiang, 2025) by indicating that task-technology fit operates along a continuum of collaboration rather than as a binary condition. AI-assisted problem-solving frequency also showed a strong association with productivity ($r = 0.462$, $r^2 = 0.213$), consistent with Nguyen (2025), who argued that agricultural decisions frequently involve edge cases requiring human intuition and lived experience.

The result also resonates with Mourtzinis et al., (2025), who found that even favorably rated AI-generated farm management plans were not free of negative expert ratings, underscoring the need for human interpretation of AI outputs. Together, these findings indicate that the value of AI lies in supporting cognitive work, such as decisions on planting, pest management, and market timing, rather than merely automating routine tasks.

This extends the Human-in-the-Loop Framework by suggesting that active problem-solving engagement is more strongly linked to productivity than passive AI use. Depth of AI integration ($r = 0.452$, $r^2 = 0.204$) was also associated with productivity, although less strongly than task sharing or problem-solving, implying that embedding AI in workflows is necessary but not sufficient; the quality and intentionality of its use matter more. Real-time AI feedback utilization showed the weakest association ($r = 0.406$, $r^2 = 0.165$) and the lowest mean score ($M = 3.30$).

This pattern is plausibly explained by unreliable electricity and connectivity, as 40.6% of respondents lacked reliable electricity and 47.8% had limited or no internet access. It is consistent with Choruma et al., (2024), who highlighted the challenges that constrain the use of digital technologies by smallholder farmers in Sub-Saharan Africa, and with Shitaye et al., (2026), who observed that AI applications in East African agriculture remain largely short-term and pilot-based. As infrastructure improves, the contribution of real-time feedback may strengthen, which constitutes an important area for future research.

Hybrid Workplace Optimization and Workforce Outcomes

Hybrid workplace optimization significantly predicted workforce outcomes, explaining 37.9% of the variance ($R^2 = 0.379$, adjusted $R^2 = 0.360$; $f^2 = 0.61$). This large effect extends Socio-Technical Systems Theory by indicating that the joint optimization of social and technical subsystems is associated with workforce outcomes even in resource-constrained settings, thereby supporting the argument of Wu & Zhong, (2025) that the next frontier of agricultural AI lies in integrated socio-technical systems rather than isolated algorithms. Training and skill development emerged as the strongest predictor ($\beta = 0.242$, $p = 0.003$), uniquely explaining 5.0% of the variance.

This finding aligns with Daum, (2025), who showed that digital tools may deskill or upskill workers depending on the training that accompanies them, and with Cao et al., (2025), who identified training as a factor shaping farmer cooperatives' intention to adopt digital technology. The present study extends this work by quantifying the unique contribution of training to workforce outcomes in a Central African setting. Given that 8.7% of respondents had no formal education and 20.3% had only primary education, training programs must accommodate diverse literacy levels.

Training is likely to build both competence and confidence, enabling workers to use AI effectively while reducing anxiety about displacement. Evidence from Benin, where extension agents' engagement with generative AI was associated with changes in advisory performance (Gouroubera et al., 2026), further suggests that building the capacity of intermediaries is an important channel through which AI benefits reach farmers in West and Central Africa.

Organizational support ($\beta = 0.212$, $p = 0.009$, $\Delta R^2 = 0.039$) was the second strongest predictor, corroborating Qorri et al., (2024), who found that firms which deliberately manage knowledge, change, and labor allocation absorb labor-saving technologies more effectively than those that treat adoption as a purely technical exercise. In Cameroon, cooperatives and extension services play a central role in providing this support by facilitating adoption, supplying resources for skill development, and creating a positive adoption climate; such support should therefore be treated as a strategic investment.

Clear role definition ($\beta = 0.198$, $p = 0.017$, $\Delta R^2 = 0.034$) contributes by reducing role ambiguity and clarifying how AI augments rather than replaces human capabilities. In Cameroon, where workers may fear that AI will displace traditional knowledge, clear communication about the complementary role of AI is essential for morale and engagement. Change management and communication ($\beta = 0.189$, $\Delta R^2 = 0.030$) and AI tools designed for ease of use ($\beta = 0.175$, $\Delta R^2 = 0.027$) made smaller but significant contributions.

The relatively weak contribution of ease of use contrasts with Cao et al., (2025), who identified perceived ease of use as an important mechanism in cooperatives' intention to adopt digital technology. A plausible explanation is that, among respondents with at least one year of AI experience, practical benefits matter more than interface sophistication; moreover, because 29.0% of respondents used only basic phones, AI services delivered through simple channels such as SMS may already provide an acceptable level of usability. This interpretation warrants further testing.

Theoretical Integration and Contributions

This study makes three key theoretical contributions. First, it extends Socio-Technical Systems Theory to Central African agriculture by demonstrating that joint optimization of technical (AI, infrastructure) and social (training, support, traditional knowledge) subsystems predicts productivity and workforce outcomes. The social subsystem including traditional knowledge, community structures, and cooperatives is particularly important and must be integrated into AI design.

In labor-intensive agricultural operations in Cameroon's Centre Region, the social subsystem includes farm workers' knowledge (both formal and traditional), experience, work relationships, adaptation capacity, and the organizational structures of cooperatives

and farmer associations, while the technical subsystem includes AI tools, data infrastructure, mobile connectivity, and automated processes. Second, the study extends Task-Technology Fit Theory by showing that task-technology fit operates along a continuum of collaboration intensity, not as a binary condition. Intentional task design and role definition enhance fit, particularly in Cameroonian agriculture where tasks require integration of formal and traditional knowledge. In labor-intensive agriculture in Cameroon, tasks vary substantially by crop type (cassava, maize, plantain, vegetables), season (wet versus dry), geographic location (lowland versus highland), and production system (smallholder versus commercial).

AI tools that fit high-frequency, data-intensive tasks such as pest detection (particularly for cassava mosaic disease and maize stem borers), irrigation scheduling, and yield prediction are more likely to be adopted and used effectively than tools that require substantial data input or do not align with existing work routines. Furthermore, the fit between AI tools and task requirements in Cameroon must account for limited digital literacy, varying educational backgrounds, and the need for interfaces that work on basic mobile phones given limited smartphone penetration in rural areas.

Third, the study extends the Human-in-the-Loop Framework by demonstrating that meaningful cognitive engagement (problem-solving, contextual judgment) matters more than passive oversight. AI systems should engage workers in interpreting and applying recommendations, building capacity and maintaining agency. In Cameroonian agricultural contexts, the Human-in-the-Loop Framework provides a practical model for optimizing human-AI collaboration, suggesting that the most effective configurations maintain human involvement at critical decision points while automating routine tasks.

The framework also emphasizes that human oversight should be designed into AI systems from the outset rather than added as an afterthought, ensuring that AI recommendations are interpretable, explainable, and actionable for agricultural workers with varying levels of formal education and digital literacy. In Cameroon, the Human-in-the-Loop Framework takes on particular significance given the importance of local ecological knowledge and traditional farming practices that cannot be fully captured by AI systems.

Managerial and Policy Implications

For managers and cooperative leaders, the positive relationship between collaboration intensity and productivity means that simply deploying AI is insufficient; intentional workflow design is essential. Given infrastructural constraints, priority should be given to AI applications that work offline or with limited connectivity (e.g., SMS-based advisories, offline decision support).

Training and skill development should be prioritized, with programs accommodating varying literacy levels and using offline materials, peer-to-peer learning, and simplified interfaces. Organizational support should leverage existing cooperative structures for peer learning and shared support. Clear role definition must explicitly acknowledge the value of traditional agricultural knowledge that AI cannot replicate.

For policymakers, supporting AI adoption requires complementary investments in digital infrastructure (electricity, internet, mobile networks), workforce development (training, digital literacy), and institutional support (extension services, cooperatives). Integrated approaches addressing the socio-technical system holistically are more effective than technology-focused subsidies alone.

Limitations and Future Research Directions

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference; longitudinal research is needed to establish causal direction. Second, self-reported measures may introduce bias; future research should incorporate objective productivity data (yields, efficiency metrics). Third, the single-region focus (Centre Region)

limits generalizability; comparative studies across Cameroonian regions and African countries are needed.

Fourth, mediating mechanisms (cognitive load, decision quality) and moderating variables (age, education, digital literacy) were not examined. Fifth, the role of traditional agricultural knowledge in AI collaboration requires specific investigation. Sixth, cost-benefit analyses are needed to determine whether productivity gains justify adoption costs.

CONCLUSION

This study concludes that human-AI collaboration intensity is significantly and positively associated with operational productivity in labor-intensive agricultural operations in Cameroon's Centre Region, with AI-human task sharing and AI-assisted problem-solving showing the strongest associations. Hybrid workplace optimization significantly predicts workforce outcomes, with training and skill development, organizational support, and clear role definition as the most influential dimensions, and these relationships hold despite substantial infrastructural constraints.

The findings imply that productivity gains from agricultural AI depend less on technology deployment alone than on deliberate task design, workforce capacity building, and institutional support. Agri-businesses, cooperatives, and extension services should therefore prioritize offline-capable tools, literacy-sensitive training, and explicit role definition, while policymakers should complement AI promotion with investment in electricity and connectivity. Longitudinal and quasi-experimental research is recommended to confirm these causal relationships.

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CONFLICT OF INTEREST

The author declares no conflict of interest. The author has no financial, commercial, or personal relationship with the developers or vendors of the AI-based decision support tools used by the respondents, nor with the agricultural enterprises, cooperatives, or the Ministry of Agriculture and Rural Development (MINADER) extension services that provided access to the sampling frames, that could be construed as influencing the design, data collection, analysis, interpretation, or reporting of this study.

AUTHOR CONTRIBUTION

Eyong Ako: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, and Project administration. As the sole author, Eyong Ako designed the study and the research instrument, coordinated pilot testing and field data collection with trained research assistants and agricultural extension officers, performed the statistical analyses in SPSS version 27.0, interpreted the results, and prepared and revised the manuscript. The author has read and approved the final version of the manuscript and is accountable for all aspects of the work.

GENERATIVE ARTIFICIAL INTELLIGENCE USAGE STATEMENT

During the preparation of this manuscript, the author used AI, a generative AI tool, to improve the language, clarity, and academic style of the text; to restructure the abstract into background, objective, method, results, and conclusion sub-sections and condense the conclusio. Generative AI was not used to collect, generate, or analyze the research data; all

statistical analyses were performed by the author using SPSS version 27.0. All AI-assisted text and every AI-suggested reference were reviewed, verified against the original sources, and edited by the author, who takes full responsibility for the content, accuracy, and integrity of this article.

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