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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

The agricultural sector in Sub-Saharan Africa faces severe labor shortages and productivity stagnation, with Cameroon's Centre Region experiencing particular challenges including 15% workforce decline over five years and only 1.5% annual productivity growth. This study investigated the relationship between human-AI hybrid workplace optimization and productivity in labor-intensive agricultural operations in Cameroon's Centre Region. A cross-sectional survey of 138 agricultural operators across 15 enterprises examined how human-AI collaboration intensity influences operational productivity and how hybrid workplace optimization affects workforce outcomes. Findings revealed significant positive relationships between collaboration intensity and productivity, with AI-human task sharing showing the strongest correlation ($r = 0.485$, $p < 0.001$). Hybrid workplace optimization significantly predicted workforce outcomes ($R^2 = 0.379$), with training and skill development emerging as the strongest predictor ($\beta = 0.242$, $p = 0.003$). This study contributes empirically to Socio-Technical Systems Theory by demonstrating that human-AI collaboration intensity is a measurable predictor of productivity outcomes in Central African agricultural contexts, extending previous research primarily focused on developed economies. The findings provide practical guidance for Cameroonian agri-businesses, cooperatives, and extension services seeking to optimize human-AI collaboration through targeted investments in training, organizational support, and clear role definition, while acknowledging infrastructural and capacity-building challenges. Given the cross-sectional design, causal relationships cannot be definitively established; future longitudinal research is recommended.

Keywords: human-AI collaboration; hybrid workplace; operational productivity; workforce outcomes; agricultural operations; cameroon; socio-technical systems; sub-saharan Africa

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 (World Bank, 2024). 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 (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 (Kempf, 2025). 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 (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 Trist et al., (2000), 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 (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, developed by Goodhue & Thompson, (1995), 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., 2025).

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. (2025) 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. (2026) 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.

Research by Kempf (2025) on FieldLark AI argues that the most powerful combination is human plus AI working together, particularly in agriculture where so many decisions are edge cases requiring intuition and lived experience. 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. (2025), Kempf (2025), and 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., 2026). 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. **Gaps:** (1) No studies quantify collaboration intensity as a distinct predictor of productivity in African agriculture; (2) Limited research on hybrid workplace optimization dimensions predicting workforce outcomes in Central Africa; (3) 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 Trist et al., (2000) original formulation 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: (1) assess the effect of human-AI collaboration intensity on operational productivity in labor-intensive agricultural operations in Cameroon's Centre Region; and (2) 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:

$\mathbf{H_1}$**:** Human-AI collaboration intensity has a significant positive influence on operational productivity in labor-intensive agricultural operations in Cameroon's Centre Region.

$\mathbf{H_2}$**:** Human-AI hybrid workplace optimization has a significant positive influence on workforce efficiency and job satisfaction among agricultural workers in Cameroon's Centre Region.

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 Approach and Design

This study adopted a quantitative research approach to investigate the relationship between human-AI hybrid workplace optimization and productivity in labor-intensive agricultural operations in Cameroon's Centre Region. The cross-sectional approach is appropriate for this study because the research objectives focus on establishing relationships between variables rather than tracking changes over time (Creswell & Creswell, 2017). However, the cross-sectional design limits causal inference, a limitation acknowledged in the discussion and conclusion sections.

The study was conducted in the Centre Region of Cameroon, specifically in three departments: Mfoundi (which includes the capital city Yaoundé and surrounding agricultural areas), Méfou-et-Afamba (an important food production zone), and Lekié (known for intensive cassava and maize cultivation) primary food production zone with intensive cassava, maize, plantain, and vegetable cultivation. Data collected January–March 2026, coinciding with main dry season agricultural activities.

The study population comprised farm managers, agri-business owners, cooperative leaders, and operations supervisors in agricultural enterprises in Cameroon's Centre Region that had implemented or were considering implementing AI-based decision support tools. Eligibility criteria included: (1) current employment in an agricultural enterprise or cooperative with at least 10 employees or members; (2) direct responsibility for or regular involvement in operational decision-making; (3) at least one year of experience with AI-based decision support tools (defined as mobile applications or computer-based systems providing recommendations on planting, pest management, irrigation, or marketing); (4) willingness to participate in the study; and (5) ability to provide informed consent.

A sample of 150 respondents was selected using stratified random sampling. Stratification was based on three criteria: (1) enterprise size (micro: <10 employees/members, small: 10-49 employees/members, medium: 50-199 employees/members, with stratification based on cooperative membership records and MINADER farm registration data); (2) type of agricultural operation (cassava production, maize cultivation, plantain farming, vegetable production, and mixed crop systems the dominant production systems in the Centre Region); and (3) years of AI technology adoption (<2 years, 2-5 years, >5 years). Within each stratum, respondents were randomly selected from lists provided by MINADER's regional agricultural extension services and from membership rosters of agricultural cooperatives in the three departments.

The sample size of 150 was determined based on power analysis for multiple regression, with an expected medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.80, requiring approximately 130 respondents for the number of predictors in the model (Cohen, 2013). The oversampling to 150 accounted for anticipated non-response and incomplete questionnaires, particularly given the challenges of data collection in rural Cameroonian contexts where transportation and communication infrastructure can be limited. Structured questionnaire in French and English, translated into Ewondo and Bassa as needed, administered via face-to-face interviews with trained research assistants and extension officers.

Sections: (A) Demographics (gender, age, education, enterprise size, AI adoption years, primary activity, electricity/internet access, mobile phone type); (B) Human-AI Collaboration Intensity (15 items, 5 dimensions); (C) Hybrid Workplace Optimization (15 items, 5 dimensions); (D) Operational Productivity (14 items, 5 indicators); (E) Workforce Outcomes (12 items, 5 indicators). All items rated on 5-point Likert scales.

This study operationalizes collaboration intensity through five dimensions: (1) frequency of AI-assisted decision-making; (2) depth of AI integration in daily operations; (3) level of AI-human task sharing; (4) real-time AI feedback utilization; and (5) AI-assisted problem-solving frequency. This multidimensional approach recognizes that collaboration intensity encompasses not only how often workers use

AI but also how deeply AI is embedded in work processes and how effectively tasks are shared between human and AI agents. This study measures operational productivity 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. This study measures workforce outcomes 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.

The questionnaire was pre-tested with 25 agricultural operators from the target population in the Centre Region who were not included in the final sample. Pilot testing served three purposes: (1) assessing clarity and comprehensibility of items, particularly given varying literacy levels and the need for translation into local languages; (2) identifying ambiguous or confusing questions; and (3) estimating reliability coefficients. Based on pilot feedback, several items were reworded for clarity, and the questionnaire length was adjusted to approximately 30-40 minutes completion time to accommodate the face-to-face interview format. The pilot test also allowed the research team to refine data collection procedures, including the use of local research assistants trained in both French and 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 (α = 0.88). The human-AI collaboration intensity scale showed good reliability (α = 0.85, with subscale α ranging from 0.77 to 0.83). The hybrid workplace optimization scale showed good reliability (α = 0.83, with subscale α ranging from 0.74 to 0.81). The operational productivity scale showed acceptable reliability (α = 0.81), and the workforce outcomes scale showed acceptable reliability (α = 0.79).

These coefficients exceed the recommended threshold of 0.70 for acceptable reliability (Nunnally, J. C., & Bernstein, 1994). Written informed consent was obtained from all participants prior to questionnaire administration. For participants with limited literacy, the information sheet was read aloud in the presence of a witness, and verbal consent was documented by the research assistant. To protect confidentiality, questionnaires were anonymized using identification codes rather than respondent names.

Data were stored on password-protected computers with access limited to the research team. Given that 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, with verbal consent recorded by the research assistant and witnessed by a third party.

Data analysis employed both descriptive and inferential statistical techniques using SPSS version 27.0.

1. **Descriptive Statistics:** Frequencies, percentages, means, and standard deviations were used to summarize respondent characteristics and responses to all scale items. Composite scores for each construct were calculated by averaging items within each dimension. **Assumption Testing:** Before conducting regression analysis, assumptions were tested as follows:
2. **Normality:** The Shapiro-Wilk test was used to assess normality of residuals. Skewness and kurtosis values were examined, with acceptable ranges of -2 to +2 for skewness and -7 to +7 for kurtosis (West et al., 1995).
3. **Multicollinearity:** Variance inflation factors (VIF) were calculated for all predictor variables, with VIF < 5 indicating no serious multicollinearity concerns (Hair Jr, et.al, 2010).
4. **Heteroscedasticity:** The Breusch-Pagan test was used to assess whether error variance was constant across levels of predictor variables, with $p > 0.05$ indicating no heteroscedasticity.
5. **Linearity:** Scatterplots of residuals versus predicted values were examined to assess the linearity assumption.
6. **Hypothesis Testing:** For Hypothesis H_1 (relationship between human-AI collaboration intensity and operational productivity), Pearson correlation analysis was conducted to examine bivariate relationships between each collaboration dimension and operational productivity.

For Hypothesis H_2 (influence of hybrid workplace optimization on workforce outcomes), multiple regression analysis was conducted with the five hybrid workplace optimization dimensions as predictor variables and overall workforce outcomes as the dependent variable. Regression models controlled for potential confounding variables including enterprise size, years in operation, education level, and access to reliable electricity and internet connectivity (factors identified in pilot testing as potentially influencing AI effectiveness in the Cameroonian context). Effect sizes were reported using R^2 and standardized beta coefficients (β). 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

Characteristic	Category	Frequency (n)	Percentage (%)
	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 scores are slightly lower than those reported in studies from developed agricultural contexts, likely reflecting the challenges of limited digital infrastructure and varying digital literacy levels in the Cameroonian setting.

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 relationships between all human-AI collaboration intensity dimensions and operational productivity. The level of AI-human task sharing showed the strongest correlation ($r = 0.485$, $p < 0.001$), explaining 23.5% of the variance in 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 ($r = 0.452$, $p < 0.001$, $r^2 = 0.204$). Real-time AI feedback utilization showed the weakest correlation ($r = 0.406$, $p < 0.001$, $r^2 = 0.165$), though still significant at $p < 0.001$.

These findings provide strong support for **Hypothesis H_1**, which posited a significant positive relationship between human-AI collaboration intensity and operational productivity in Cameroonian agricultural operations. The results demonstrate that all dimensions of collaboration intensity are positively associated with productivity, with task sharing and problem-solving frequency showing particularly strong relationships. The pattern of findings is similar to that observed in studies from developed agricultural contexts (Fügener et al., 2026), though the effect sizes are slightly smaller potentially reflecting the infrastructural and capacity-building challenges that characterize AI adoption in Central Africa.

The practical significance of these correlations is noteworthy. The effect sizes (r^2) indicate that collaboration intensity dimensions explain between 16.5% and 23.5% of the variance in operational productivity, suggesting that collaboration intensity is a meaningful predictor of productivity outcomes even in resource-constrained settings. For example, the r^2 of 0.235 for AI-human task sharing means that nearly one-quarter of the variation in operational productivity can be explained by the level of task sharing between humans and AI systems a practically significant 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 Cohen, (2013) 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 provide strong support for **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 ($R^2 = 0.379$) indicates that hybrid workplace optimization is a practically meaningful predictor of workforce outcomes in Cameroonian agricultural operations, consistent with findings from other contexts (Cao et al., 2025; Qorri et al., 2024).

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 of Results

Discussion of Objective One: 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 aligns with Fügener et al., (2026), who show that AI augments rather than replaces human expertise. However, our study extends this work by providing quantitative evidence from Central Africa that collaboration *intensity* not merely presence or absence matters for productivity, even amid infrastructural constraints. The strongest correlation was between AI-human task sharing and productivity ($r = 0.485$, $r^2 = 0.235$).

This suggests that clearly defined collaboration structures where tasks are systematically divided based on each party's strengths enhance productivity more than simply increasing AI usage frequency. In Cameroon, given limited digital infrastructure, organizations should prioritize optimizing *quality* of task sharing over increasing AI usage. This extends Task-Technology Fit Theory by showing that task-technology fit operates along a continuum, not as a binary condition.

AI-assisted problem-solving frequency also showed strong correlation ($r = 0.462$, $r^2 = 0.213$), consistent with Kempf (2025). This finding indicates that AI's value lies in enhancing cognitive work, not merely automating routine tasks. Even with limited infrastructure, AI supports critical decisions about planting, pest management, and market timing. This extends the Human-in-the-Loop Framework by demonstrating that meaningful problem-solving engagement drives productivity more than passive AI use.

Depth of AI integration ($r = 0.452$, $r^2 = 0.204$) predicted productivity but less strongly than task sharing or problem-solving. Embedding AI in workflows is necessary but insufficient; quality and intentionality matter more. In Cameroon, unreliable electricity and connectivity make deep integration challenging, reinforcing the importance of focusing on task sharing and problem-solving quality. Real-time feedback showed the weakest correlation ($r = 0.406$, $r^2 = 0.165$). This may reflect the immaturity of real-time systems in Central African agriculture and limited internet access (47.8% of respondents lacked connectivity). As infrastructure improves, this relationship may strengthen an important area for future research.

Discussion of Objective Two: Hybrid Workplace Optimization and Workforce Outcomes

Hybrid workplace optimization significantly predicted workforce outcomes, explaining 37.9% of variance ($R^2 = 0.379$, Adjusted $R^2 = 0.360$). This large effect size extends Socio-Technical Systems Theory by demonstrating that joint optimization of social and technical systems predicts workforce outcomes even in resource-constrained settings. Training and skill development emerged as the strongest predictor ($\beta = 0.242$, $p = 0.003$), uniquely explaining 5.0% of variance.

This aligns with Daum, (2025) and extends that work by quantifying training's specific contribution. Given that 8.7% of respondents had no formal education and 20.3% only primary education, training programs must accommodate diverse literacy levels. Training builds both competence and confidence, enabling workers to use AI effectively while reducing anxiety about displacement.

Organizational support ($\beta = 0.212$, $p = 0.009$, $\Delta R^2 = 0.039$) corroborates (Qorri et al., 2024). In Cameroon, cooperatives and extension services play critical roles in facilitating adoption. Support reduces anxiety, provides resources for skill development, and creates positive adoption climates. This support should be treated as strategic investment. Clear role definition ($\beta = 0.198$, $p = 0.017$, $\Delta R^2 = 0.034$) reduces role ambiguity by clarifying how AI augments rather than replaces human capabilities.

In Cameroon, workers may fear AI will replace traditional knowledge; clear communication about AI's complementary role is essential for morale and engagement. AI tools designed for ease of use ($\beta = 0.175$, $\Delta R^2 = 0.027$) and change management ($\beta = 0.189$, $\Delta R^2 = 0.030$) made smaller but significant contributions. Given that 29.0% used only basic phones, workers prioritize practical benefits over interface sophistication an important insight for AI design in African contexts.

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 investigated the relationship between human-AI hybrid workplace optimization and productivity in labor-intensive agricultural operations in Cameroon's Centre Region. Findings establish that human-AI collaboration intensity significantly influences operational productivity, with task sharing and problem-solving frequency as strongest correlates. Hybrid workplace optimization significantly enhances workforce outcomes, with training, organizational support, and role definition as key predictors. These relationships hold despite infrastructural constraints.

Recommendations for Future Research Based on the limitations and findings of this study, First, longitudinal studies are needed to establish causal relationships between collaboration intensity, hybrid workplace optimization, and organizational outcomes. Second, experimental or quasi-experimental designs could provide stronger causal evidence. Finally, as digital infrastructure in Cameroon continues to improve with the ongoing expansion of electricity access and mobile internet coverage future research should examine how improvements in infrastructure moderate the relationships observed in this study.

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