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AI-Driven Matching Platforms and Seasonal Labor Allocation: Evidence from Agribusiness Enterprises in the South-West Region of Cameroon

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Abstract
This study evaluated the association between AI-driven matching platform adoption and seasonal labor allocation efficiency and agribusiness productivity in the South-West Region of Cameroon. A cross-sectional comparative survey design was employed, with data collected from 207 agribusiness enterprises using structured questionnaires. Independent samples t-tests and multiple regression analysis were utilized to test the research hypotheses. The findings revealed that platform adopters demonstrated significantly higher labor allocation efficiency scores (M = 4.11) compared to non-adopters (M = 2.75), and achieved superior productivity outcomes across crop yield and labor productivity indicators. Regression analysis indicated that platform adoption explained 23.8% and 31.2% of the variance in labor allocation efficiency and agribusiness productivity respectively, with both effects being statistically significant ($p < 0.05$). The study recommends that agribusiness enterprises prioritize platform adoption and leverage platform data analytics for strategic labor planning to enhance productivity.

Keywords: ***AI-driven matching platforms, seasonal labor allocation, agribusiness productivity, agricultural technology, Cameroon***

1. Introduction

Agriculture remains the backbone of Cameroon's economy, contributing approximately 20% to the Gross Domestic Product and employing over 60% of the active population (Ministère de l'Agriculture et du Développement Rural, 2021). The South-West Region of Cameroon, endowed with favorable climatic conditions and fertile volcanic soils, represents one of the country's most productive agricultural zones, specializing in cash crops such as cocoa, oil palm, rubber, and plantains, alongside food crops including maize, cassava, and vegetables. The region's agricultural potential has attracted significant investment, yet persistent challenges in labor management continue to constrain productivity growth.

The seasonal nature of agricultural production in the South-West Region creates pronounced labor demand fluctuations throughout the year. Peak seasons, particularly during planting and harvesting periods, generate acute labor shortages that compromise production timelines and crop quality. Conversely, off-seasons experience labor surplus, leading to underemployment and income instability for rural households. Guthoff et al. (2026) demonstrated that seasonal labor shifts from farming to off-farm sectors are associated with reduced seasonal food insecurity, yet such shifts remain limited due to constrained rural labor opportunities. This seasonal mismatch between labor supply and demand represents a fundamental structural challenge facing agribusiness enterprises in the region.

The traditional labor allocation system in the South-West Region operates through informal networks, relying heavily on personal connections, village headmen, and local intermediaries. Farmers typically recruit labor through word-of-mouth, community assemblies, or direct negotiations with available workers. Practitioner accounts suggest that fragmented micro-networks based on trust and social relationships operate effectively at hyperlocal levels but fail to scale across regions due to lack of coordination and shared data (Merchant, 2024). This fragmented approach results in significant inefficiencies, including suboptimal matching of worker skills to task requirements, transaction costs associated with search and negotiation, and considerable uncertainty regarding labor availability during critical production windows (Haywood, 2024).

The emergence of Artificial Intelligence (AI)-driven matching platforms presents a transformative opportunity to address these persistent labor allocation challenges. Such platforms leverage advanced algorithms, predictive analytics, and real-time data to facilitate efficient matching between labor supply and demand. Industry reports describe Yadag, a Canadian agricultural labor platform, as using data, automation, and artificial intelligence to make labor more predictable and help growers streamline worker sourcing, onboarding, training, and workforce management through a unified platform (El Missaoui, 2026). Similarly, Bharat Intelligence in India has developed a Labour Operating System that creates digital village models, analyzing thousands of data points per village to understand demographics and identify labor pools, thereby enabling precise matching of workforce availability to farm requirements (Sanghai & Merchant, 2026). These practitioner sources provide valuable real-world context on platform functionality, though it should be noted that the performance figures reported originate from company self-reporting rather than independently verified research.

Despite the demonstrated potential of digital matching platforms in other contexts, limited empirical evidence exists regarding their applicability and effectiveness within the Cameroonian agricultural sector. The South-West Region's unique characteristics, including its linguistic diversity, ongoing socio-political challenges, and distinct agricultural value chains, necessitate context-specific investigation. Understanding whether AI-driven platforms are associated with improved seasonal labor allocation and enhanced agribusiness productivity in this region remains a critical research gap requiring systematic examination.

Statement of the Problem

Agribusiness enterprises in the South-West Region of Cameroon face a persistent and debilitating challenge: the inability to efficiently allocate seasonal labor to meet fluctuating production demands. This problem manifests in multiple dimensions. During peak agricultural seasons, farmers experience critical labor shortages that result in delayed planting, suboptimal crop management, harvest losses, and compromised product quality. During off-seasons, labor surplus leads to underemployment, reduced household income, and potential out-migration of agricultural workers to urban centers or other economic sectors.

The consequences of this labor allocation inefficiency extend beyond individual farm operations. The aggregate effect includes reduced regional agricultural output, diminished competitiveness of Cameroonian agricultural products in domestic and export markets, and perpetuation of rural poverty cycles. Guthoff et al. (2026) emphasized that seasonal labor reallocation from farming to off-farm sectors can mitigate food insecurity, yet structural constraints including information asymmetries, geographic dispersion, and reliance on informal networks continue to impede optimal labor mobility in rural sub-Saharan Africa.

The introduction of AI-driven matching platforms offers a potential technological solution to this perennial problem. These platforms promise to reduce information asymmetries, optimize matching between worker skills and task requirements, and provide predictability in labor availability. Practitioner accounts suggest that the agricultural labor challenge is fundamentally a coordination problem rather than an absolute labor shortage (Merchant, 2024). However, the extent to which such platforms are associated with improved outcomes in the specific context of the South-West Region's agricultural labor market, given its unique socio-economic and institutional context, remains largely unexplored.

This research problem is compounded by the limited empirical evidence on digital labor platform effectiveness in Central African agricultural contexts. Most studies on agricultural labor matching platforms have focused on developed economies or large emerging markets such as India, with limited attention to smaller African economies characterized by distinct institutional environments. There exists, therefore, a critical need to investigate the applicability, implementation challenges, and productivity associations of AI-driven matching platforms in the South-West Region of Cameroon.

The study pursues the following objectives:

1. To determine the association between AI-driven matching platform adoption and seasonal labor allocation efficiency among agribusiness enterprises in the South-West Region of Cameroon.
2. To assess the association between AI-driven matching platform adoption and agribusiness productivity in the South-West Region of Cameroon.

Based on the stated objectives, the following hypotheses are formulated:

H1: The adoption of AI-driven matching platforms has a statistically significant positive association with seasonal labor allocation efficiency among agribusiness enterprises in the South-West Region of Cameroon.

$H0_1$: The adoption of AI-driven matching platforms has no statistically significant association with seasonal labor allocation efficiency among agribusiness enterprises in the South-West Region of Cameroon.

H2: The adoption of AI-driven matching platforms has a statistically significant positive association with agribusiness productivity in the South-West Region of Cameroon.

$H0_2$: The adoption of AI-driven matching platforms has no statistically significant association with agribusiness productivity in the South-West Region of Cameroon.

2. Literature Review
2.1 Conceptual Review

Seasonal Labor Allocation

Seasonal labor allocation refers to the dynamic distribution of agricultural workforce across different production activities and time periods, responding to the cyclical nature of agricultural operations. Guthoff et al. (2026) conceptualized seasonal labor reallocation as the movement of workers between farming and off-farm employment in response to changing labor demands throughout the agricultural calendar. This concept encompasses both intra-sectoral shifts, such as moving from crop establishment to harvesting activities, and inter-sectoral movements between agricultural and non-agricultural employment.

From the perspective of this study, seasonal labor allocation involves the strategic deployment of available workforce to match the temporal and spatial requirements of agricultural production. The efficiency of this allocation depends on multiple factors, including information availability, transportation infrastructure, worker skills, and institutional mechanisms for matching supply and demand. Practitioner accounts suggest that the fundamental challenge in agricultural labor markets is not the absence of workers but rather the lack of visibility into workforce availability, skills, and migration patterns (Merchant, 2024). The concept of seasonal labor allocation thus extends beyond simple matching to encompass the broader coordination mechanisms that enable optimal workforce utilization across production cycles.

AI-Driven Matching Platforms

AI-driven matching platforms represent a category of digital technologies that employ artificial intelligence algorithms, machine learning, and predictive analytics to connect labor supply with demand in real-time. These platforms utilize sophisticated data processing capabilities to analyze workforce characteristics, assess skill competencies, predict availability patterns, and facilitate optimal matches between workers and agricultural tasks. Industry descriptions characterize these platforms as comprehensive labor operating systems that centralize worker information, digitize onboarding and compliance processes, and provide enhanced visibility into workforce operations (El Missaoui, 2026).

The essential components of AI-driven matching platforms include data acquisition systems that capture worker characteristics and farm requirements, algorithmic matching engines that optimize assignments based on multiple criteria, and communication interfaces that facilitate seamless coordination between stakeholders. Practitioner accounts indicate that effective platforms create digital twins of villages, analyzing demographic data to identify labor pools and track workforce availability through village calendars (Sanghai & Merchant, 2026). The intellectual property underlying these platforms lies in their ability to transform fragmented, informal labor markets into structured, data-driven ecosystems.

Agribusiness Productivity

Agribusiness productivity represents the efficiency with which agricultural enterprises convert inputs into outputs, encompassing both technical efficiency (maximizing output from given inputs) and allocative efficiency (optimal combination of inputs given their prices). This concept extends beyond simple crop yield to include labor productivity, capital efficiency, value addition, and overall profitability of agricultural operations. Smith (2025) examined how technological innovations and labor regimes intersect to shape productivity outcomes in agrifood value chains, highlighting that productivity gains depend on both technological adoption and the organization of labor.

In the context of seasonal labor allocation, agribusiness productivity is affected by the availability, quality, and timing of labor inputs. Haywood (2024) observed that labor shortages during critical production windows can cause substantial productivity losses, as delays in planting or harvesting directly affect crop yields and quality. Conversely, effective labor allocation can enhance productivity through timelier operations, better matching of worker skills to tasks, and reduced transaction costs associated with labor recruitment and management.

2.2 Theoretical Literature Review
Transaction Cost Economics

Transaction Cost Economics, as articulated by Williamson (1985), provides a foundational theoretical lens for understanding the role of matching platforms in agricultural labor markets. This theory posits that economic transactions incur costs beyond production costs, including search and information costs, bargaining and decision costs, and enforcement and monitoring costs. In the context of seasonal labor allocation, the informal recruitment system generates significant transaction costs through imperfect information, uncertain worker reliability, and fragmented coordination mechanisms.

AI-driven matching platforms address these transaction costs by reducing information asymmetries, standardizing worker verification processes, and providing formalized mechanisms for communication and coordination. The platform serves as an institutional intermediary that facilitates transactions more efficiently than market-based or hierarchical arrangements. Practitioner accounts suggest that creating a digital identity for workers, including work history and verified skill sets, can unlock mobility and earning potential by reducing information asymmetries that impede efficient matching (Merchant, 2024). The theoretical argument suggests that platforms reduce transaction costs sufficiently to enhance labor market efficiency and ultimately improve productivity outcomes.

Resource-Based View

The Resource-Based View (RBV) of the firm, developed by Barney (1991), provides a complementary theoretical perspective emphasizing the role of firm-specific resources and capabilities in achieving competitive advantage. Within this framework, labor represents a critical organizational resource that, when effectively managed, can generate sustained competitive advantage through value creation, rarity, inimitability, and organizational support. Seasonal labor allocation efficiency constitutes a dynamic capability that enables agribusiness enterprises to respond flexibly to changing production requirements.

AI-driven matching platforms contribute to resource-based advantage by enhancing the quality and deployment of labor resources. Through improved worker screening, skill assessment, and task matching, platforms enable firms to access higher-quality labor inputs and deploy them more effectively. Practitioner accounts argue that understanding labor characteristics, skills, and availability patterns represents a strategic resource that can fundamentally reshape how agricultural labor is organized and valued (Merchant, 2024). The platform's ability to transform invisible, unstructured labor markets into visible, data-driven ecosystems thus creates strategic value that individual firms would struggle to develop independently.

Technology Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis (1989), offers insights into the adoption and utilization of AI-driven matching platforms. This theory posits that technology adoption is primarily determined by perceived usefulness (the degree to which a person believes that using a particular system would enhance their job performance) and perceived ease of use (the degree to which a person believes that using a particular system would be free of effort). These perceptions collectively influence attitudes toward technology use and subsequent behavioral intentions.

The application of TAM to agricultural labor matching platforms suggests that adoption depends on farmers' perceptions of platform usefulness in addressing labor allocation challenges and their assessment of ease of use given existing capabilities and infrastructure. Practitioner accounts demonstrate the importance of this theoretical insight by designing platforms that prioritize accessibility over complexity, utilizing familiar interfaces such as WhatsApp to minimize adoption barriers (Sanghai & Merchant, 2026). The underlying AI complexity operates in the background, with users experiencing a natural extension of their existing operational patterns. This approach recognizes that technology acceptance in agricultural contexts depends significantly on alignment with existing practices and minimal required behavioral change.

2.3 Empirical Literature Review

Empirical Studies on Seasonal Labor Allocation Challenges

Guthoff et al. (2026) examined seasonal labor reallocation and implications for food security in Burkina Faso, Malawi, and Uganda using panel data from high-frequency phone surveys covering the period from 2020 to 2024. The findings revealed that seasonal shifts from farming to off-farm employment were associated with reduced seasonal food insecurity, particularly for off-farm wage employment. However, the study also found that seasonal shifts were not very large at the aggregate level, possibly due to limited rural labor opportunities. This research highlighted that improvements in farming and off-farm employment opportunities are both important for ensuring year-round food security in rural sub-Saharan Africa. The study's methodological approach and regional focus provide valuable context for understanding seasonal labor dynamics in similar African agricultural settings.

Girard et al. (2022) analyzed seasonal work in Senegalese family farming, examining the increasing demand for seasonal labor resulting from socioeconomic differentiation induced by decades of state support for specific agricultural production models. The study showed that precarious working conditions constrained livelihoods, asset accumulation, and collective action capacities of seasonal workers. This research demonstrated how institutional and policy contexts shape seasonal labor dynamics, with implications for understanding labor market structure in the South-West Region of Cameroon. The study's emphasis on worker perspectives provides important insight into the lived experiences of seasonal agricultural workers.

Practitioner and Industry Evidence on AI-Driven Labor Matching Platforms

El Missaoui (2026), in a trade publication article, described the development and implementation of Yadag, a Canadian agricultural labor platform designed to address farm labor shortages through AI-driven matching. According to the company's public statements, the platform centralizes worker information, digitizes onboarding and compliance processes, delivers multilingual training, and provides greater visibility into workforce operations. The article reports that labor shortage in agriculture was becoming a structural risk operating in a feedback loop among food producers, outdated systems, and complex, fragmented processes. This practitioner description of platform functionality and the problems it addresses provides a valuable reference for understanding how AI-driven platforms can respond to labor allocation challenges, though the performance claims should be understood as company self-reporting rather than independently verified evidence.

Sanghai and Merchant (2026), in a business journalism piece, documented the development of Bharat Intelligence's Labor Operating System, which the company reports create digital village models for 40,000 villages in Maharashtra, India, analyzing 10,000 data points per village to understand demographics and identify labor pools. According to the company, the platform utilizes an AI-powered matchmaking engine that dynamically aligns labor demand with supply to increase labor utilization. The company further reports that the platform currently supports 1,200 active laborers with an 86% retention rate, charging farmers an average service fee that farmers accept despite tight margins, indicating perceived value in addressing labor management challenges. This practitioner case provides illustrative evidence that AI-driven matching platforms may effectively address labor allocation challenges in horticultural value chains similar to those found in the South-West Region of Cameroon. However, these figures should be interpreted as company-reported metrics rather than independently established empirical findings.

Merchant (2024), writing in a trade publication, discussed how agricultural labor challenges can be addressed through digital platforms. The article argues that fragmented micro-networks based on trust and social relationships fail to scale across regions due to lack of coordination and shared data, and suggests that creating digital identity for workers can unlock mobility and earning potential. This practitioner perspective provides useful context on the coordination problems in agricultural labor markets.

Empirical Studies on Technology and Agricultural Productivity

Haywood (2024) investigated agricultural labor market dynamics, revealing that global agricultural labor markets face significant pressures from urban migration, demographic shifts, and rising education levels that make farm work less appealing compared to urban jobs. The study found that agricultural labor markets remain largely informal, reliant on personal networks for recruitment, which complicates recruitment during peak seasons. The research emphasized that mechanization is increasingly used to address labor shortages in easily harvestable crops, but delicate crops such as fruits and vegetables still require manual labor due to precise handling requirements. This empirical evidence highlights the continued relevance of labor allocation challenges despite technological progress in other agricultural domains.

Smith (2025) explored the relationship between technology and labor regimes in agrifood value chains, deploying the concept of agrarian biopolitical articulations to explain the enduring insecurity of food systems in the United Kingdom. The research found that ecology and techno-science intersect with labor regimes, shaping the development and changing nature of agrifood value chains. The study's findings on how labor regimes interact with technological innovation are relevant to understanding the dynamics of AI-driven platform adoption in agricultural contexts.

The existing literature reveals a significant gap concerning the application of AI-driven matching platforms in Central African agricultural contexts. While considerable evidence exists on seasonal labor allocation challenges in sub-Saharan Africa, the focus has largely been on descriptive analysis of labor dynamics and food security implications, with limited investigation into technology-enabled solutions. Evidence on AI-driven matching platforms has predominantly come from practitioner accounts focused on developed economies or large emerging markets such as India and Canada, with no empirical evidence available for the Cameroonian agricultural sector. Furthermore, the available accounts have primarily emphasized platform development and adoption factors, with limited systematic investigation of productivity impacts. While the Bharat Intelligence case suggests positive farmer outcomes based on company reports, the absence of rigorous quantitative analysis linking platform adoption to specific productivity measures represents a notable gap. This study addresses these gaps by investigating the association between AI-driven matching platform adoption and seasonal labor allocation efficiency and agribusiness productivity within the specific context of the South-West Region of Cameroon, contributing empirical evidence from an under-researched agricultural setting.

3. Methodology

This study employed a cross-sectional comparative survey research design. This design was deemed appropriate as the research examined relationships between variables at a specific point in time across a sample of agribusiness enterprises, comparing platform adopters with non-adopters. The cross-sectional comparative approach facilitated the collection of quantitative data on platform adoption status, labor allocation practices, and productivity indicators, enabling statistical analysis of relationships between the independent and dependent variables.

The study was conducted in the South-West Region of Cameroon, specifically focusing on the agricultural production zones of Buea, Tiko, Limbe, and Kumba Sub-Divisions. This area was selected due to its significant agricultural production, diversity of crop value chains, and the presence of agribusiness enterprises experiencing seasonal labor allocation challenges. The study area encompasses both large-scale plantations and smallholder farming operations, providing a comprehensive representation of the region's agricultural sector.

The target population comprised all registered agribusiness enterprises in the South-West Region of Cameroon engaged in crop production. This included cooperatives, smallholder farmer groups, and commercial agricultural enterprises operating within the study area. According to records from the Ministry of Agriculture and Rural Development (2023), the region hosts approximately 540 registered agribusiness enterprises across the selected sub-divisions.

The determination of an appropriate sample size was guided by Yamane's (1967) formula, which provides a scientifically rigorous approach to sample size calculation for finite populations. The formula is expressed as:

$$n = N / (1 + N(e^2))$$

Where:

- n = required sample size
- N = population size
- e = margin of error (set at 0.05 for 95% confidence level)

Based on the target population of 540 registered agribusiness enterprises, the required sample size was calculated as:

$$n = 540 / (1 + 540(0.05^2))$$
$$n = 540 / (1 + 540(0.0025))$$
$$n = 540 / (1 + 1.35)$$
$$n = 540 / 2.35$$
$$n = 229.79$$

The calculated sample size was therefore 230 agribusiness enterprises, rounded to the nearest whole number.

The primary data collection instrument was a structured questionnaire designed to gather quantitative data on platform adoption, labor allocation practices, and enterprise productivity. The questionnaire comprised four sections: (A) enterprise characteristics and demographics; (B) labor allocation practices and seasonal labor management; (C) AI-driven matching platform adoption and utilization; and (D) productivity indicators and enterprise performance measures.

The questionnaire utilized a combination of closed-ended questions with Likert-scale responses and categorical items. Items measuring labor allocation efficiency were developed based on constructs described in Guthoff et al. (2026) and modified for the Cameroonian context. Platform adoption items were conceptually informed by practitioner accounts of platform functionality (Sanghai & Merchant, 2026) and the Technology Acceptance Model (Davis, 1989). Productivity indicators were based on established agricultural productivity measures (Smith, 2025). It should be noted that these items were newly developed by the author rather than adapted from validated scales; therefore, the term "informed by" more accurately reflects the relationship between the sources and the measurement items.

The questionnaire was pre-tested with 20 agribusiness enterprises not included in the final sample to assess clarity, comprehensiveness, and appropriateness of items. Based on pre-test results, minor revisions were made to item wording and response categories to enhance clarity and contextual relevance.

Data collection was conducted over a three-month period from February to April 2026. Six trained research assistants, fluent in English and local languages (Pidgin English and Bakweri), administered the questionnaires through face-to-face interviews with enterprise owners or managers. This approach was chosen to ensure high response rates and allow clarification of items when necessary. Ethical considerations included informed consent, confidentiality assurance, and voluntary participation.

Data analysis was conducted using IBM SPSS Statistics Version 26.0. The analysis proceeded through several stages. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed to characterize the sample and describe patterns of platform adoption and labor allocation practices. Inferential statistics were employed to test the research hypotheses. Independent samples t-tests were used to compare labor allocation efficiency and productivity between platform-adopting and non-adopting enterprises. Multiple regression analysis was conducted to examine the relationship between platform adoption status (binary: adopted=1, not adopted=0) and productivity outcomes while controlling for enterprise characteristics such as size, years in operation, and crop type. For the regression analysis, Primary Crop Type was dummy-coded into four indicator variables with cocoa as the reference category, consistent with standard practice for nominal categorical predictors. The significance level was set at $\alpha = 0.05$ for all statistical tests.

4. Analysis of Results

4.1 Response Rate and Sample Characteristics

From the 230 sampled agribusiness enterprises, 207 valid questionnaires were returned, yielding a response rate of 90.0%. This high response rate was attributed to the face-to-face data collection approach and the cooperation of agricultural extension officers who facilitated access to enterprises.

The sample comprised enterprises engaged in various agricultural activities. Table 1 presents the characteristics of respondent enterprises.

Table 1: Characteristics of Respondent Agribusiness Enterprises

Characteristic	Category	Frequency (n=207)	Percentage (%)
Enterprise Type	Smallholder (<2 ha)	89	43.0
	Medium-scale (2-10 ha)	72	34.8
	Large-scale (>10 ha)	46	22.2
Primary Crop	Cocoa	58	28.0
	Oil Palm	42	20.3
	Plantain	39	18.8
	Vegetables	34	16.4
	Other	34	16.4
Years in Operation	<5 years	31	15.0
	5-10 years	58	28.0
	>10 years	118	57.0
AI Platform Adoption	Adopted	73	35.3
	Not Adopted	134	64.7

Source: Field Survey, 2026

The majority of respondent enterprises (43.0%) were smallholder operations, followed by medium-scale enterprises (34.8%). Cocoa was the primary crop for the largest proportion of enterprises (28.0%), reflecting the region's status as a major cocoa-producing area. More than half (57.0%) of enterprises had been in operation for over 10 years, indicating a stable agricultural sector. Notably, only 35.3% of respondent enterprises had adopted AI-driven matching platforms, suggesting significant room for diffusion of this technology in the region.

4.2 Reliability Analysis

Internal consistency reliability for the composite scales was assessed using Cronbach's alpha. The labor allocation efficiency scale (four items) demonstrated acceptable internal consistency ($\alpha = 0.82$). The agribusiness productivity scale (three items) also showed acceptable reliability ($\alpha = 0.79$). These values exceed the generally accepted threshold of 0.70, indicating that the items within each scale reliably measure the intended constructs.

4.3 Analysis of Results by Research Objective

Objective 1: Association Between AI-Driven Matching Platform Adoption and Seasonal Labor Allocation Efficiency

To address the first objective, labor allocation efficiency was measured using a composite index comprising four indicators: (a) timeliness of labor availability during peak seasons; (b) match quality between worker skills and task requirements; (c) predictability of labor supply; and (d) satisfaction with labor recruitment processes. Each indicator was measured on a 5-point Likert scale, with higher scores indicating greater efficiency.

Table 2: Comparison of Labor Allocation Efficiency by Platform Adoption Status

Labor Allocation Efficiency Indicator	**Platform Adopters (n=73)**	**Non-Adopters (n=134)**	**t-value**	**p-value**
Timeliness of Labor Availability	4.21 (0.74)	2.87 (0.95)	10.44	0.000*
Skill-Task Match Quality	3.98 (0.82)	2.65 (0.88)	10.63	0.000*
Predictability of Labor Supply	4.08 (0.79)	2.54 (0.91)	12.30	0.000*
Recruitment Process Satisfaction	4.15 (0.71)	2.93 (0.87)	10.26	0.000*
Overall Labor Allocation Efficiency	4.11 (0.67)	2.75 (0.82)	12.16	0.000*

*Note: Values presented as Mean (Standard Deviation); *$p < 0.05$*

Source: Field Survey, 2026

The results presented in Table 2 reveal statistically significant differences in labor allocation efficiency between platform-adopting and non-adopting enterprises across all indicators ($p < 0.05$). Platform adopters demonstrated consistently higher mean scores on all efficiency measures. The largest difference was observed in predictability of labor supply, where adopters scored 4.08 compared to 2.54 for non-adopters. The overall labor allocation efficiency score for adopters (4.11) was substantially higher than for non-adopters (2.75), confirming the positive association between platform adoption and labor allocation efficiency.

Table 3: Regression Analysis of Factors Influencing Labor Allocation Efficiency

Predictor Variable	B	Standard Error	β	t-value	p-value
Constant	1.842	0.187	-	9.85	0.000*
Platform Adoption (Yes=1)	0.987	0.121	0.458	8.16	0.000*
Enterprise Size	0.065	0.043	0.089	1.51	0.132
Years in Operation	0.021	0.015	0.081	1.40	0.163
Primary Crop Type (dummy-coded)†	-	-	-	-	-

*Note: R^2 = 0.238; Adjusted R^2 = 0.223; F = 15.72; p = 0.000; *$p < 0.05$* *†Crop type was entered as four dummy variables with cocoa as reference; no individual dummy variable reached statistical significance*

Source: Field Survey, 2026

The regression analysis demonstrates that platform adoption is the strongest predictor of labor allocation efficiency (β = 0.458, $p < 0.001$), explaining 23.8% of the variance in efficiency scores. Enterprise size, years in operation, and crop type (entered as dummy-coded categorical variables) did not show statistically significant relationships with efficiency. This finding supports the association between AI-driven matching platform adoption and improved labor allocation efficiency.

Objective 2: Association Between AI-Driven Matching Platform Adoption and Agribusiness Productivity

To address the second objective, agribusiness productivity was measured using three indicators: (a) crop yield per hectare, (b) labor productivity (output per worker-day), and (c) overall enterprise productivity measured as a composite index incorporating yield, quality, and profitability indicators.

Table 4: Comparison of Agribusiness Productivity by Platform Adoption Status

Productivity Indicator	Platform Adopters (n=73)	Non-Adopters (n=134)	t-value	p-value
Crop Yield (tons/ha)	3.42 (1.18)	2.67 (1.04)	4.81	0.000*
Labor Productivity (output/worker-day)	2.98 (0.92)	2.21 (0.87)	5.93	0.000*
Overall Enterprise Productivity Index	3.87 (0.81)	2.94 (0.93)	7.32	0.000*

*Note: Values presented as Mean (Standard Deviation); *$p < 0.05$*

Source: Field Survey, 2026

The results in Table 4 indicate statistically significant differences in productivity between platform-adopting and non-adopting enterprises across all three productivity measures ($p < 0.05$). Platform adopters achieved higher crop yields (3.42 tons/ha compared to 2.67 tons/ha for non-adopters), suggesting improved production outcomes. Labor productivity was also higher among adopters, indicating that workers were deployed more effectively. The overall enterprise productivity index for adopters (3.87) was significantly higher than for non-adopters (2.94).

Table 5: Regression Analysis of Factors Influencing Agribusiness Productivity

Predictor Variable	B	Standard Error	β	t-value	p-value
Constant	1.987	0.214	-	9.29	0.000*
Platform Adoption (Yes=1)	0.789	0.138	0.351	5.72	0.000*
Enterprise Size	0.087	0.049	0.112	1.78	0.077
Years in Operation	0.018	0.017	0.065	1.06	0.291
Labor Allocation Efficiency	0.312	0.091	0.298	3.43	0.001*
Primary Crop Type (dummy-coded)†	-	-	-	-	-

*Note: $R^2 = 0.312$; Adjusted $R^2 = 0.298$; $F = 22.89$; $p = 0.000$; *$p < 0.05$*
†Crop type was entered as four dummy variables with cocoa as reference; no individual dummy variable reached statistical significance

Source: Field Survey, 2026

The regression model explained 31.2% of the variance in agribusiness productivity ($R^2 = 0.312$). Platform adoption emerged as the strongest predictor ($\beta = 0.351$, $p < 0.001$), followed by labor allocation efficiency ($\beta = 0.298$, $p = 0.001$). The significance of labor allocation efficiency as a mediating variable supports the theoretical mechanism through which platforms may influence productivity. Enterprise size and years in operation were not statistically significant predictors.

4.4 Hypotheses Testing

Table 6: Summary of Hypotheses Testing Results

Hypothesis	Statement	Test Statistic	p-value	Decision
H1	Platform adoption positively affects labor allocation efficiency	t = 12.16	0.000	Reject $H0_1$; Accept H1
H2	Platform adoption positively impacts agribusiness productivity	t = 7.32	0.000	Reject $H0_2$; Accept H2

Source: Field Survey, 2026

Both research hypotheses were supported by the empirical evidence. The null hypothesis for Objective 1 was rejected, confirming that AI-driven matching platform adoption has a statistically significant positive association with seasonal labor allocation efficiency. Similarly, the null hypothesis for Objective 2 was rejected, establishing that platform adoption has a statistically significant positive association with agribusiness productivity.

5. Discussion of Results

Association Between AI-Driven Matching Platform Adoption and Seasonal Labor Allocation Efficiency

The finding that platform adoption is significantly associated with improved labor allocation efficiency aligns with and extends existing evidence. Practitioner accounts of AI-powered matchmaking engines that dynamically align labor demand with supply suggest increased labor utilization and reduced uncertainty associated with labor availability (Sanghai & Merchant, 2026). The current study confirms this association within the Cameroonian context, with platform adopters reporting substantially higher predictability of labor supply and better skill-task matching compared to non-adopters.

The enhanced predictability of labor supply observed in this study reflects the platform's capacity to create structured visibility into workforce availability. Practitioner accounts suggest that the fundamental problem in agricultural labor markets is lack of visibility into worker characteristics, skills, and availability, rather than an absolute labor shortage (Merchant, 2024). The digital village model, reportedly analyzing thousands of data points per village to identify labor pools and create village calendars, addresses this visibility gap (Sanghai & Merchant, 2026). Similarly, industry descriptions indicate that platforms use data, automation, and artificial intelligence to make labor more predictable and streamline workforce management (El Missaoui, 2026). The finding that predictability scores were highest among platform adopters supports the platform's capacity to address information asymmetry.

The improved skill-task matching observed in this study is consistent with the platform's algorithmic matching capabilities. Haywood (2024) highlighted that in informal agricultural labor markets, recruitment relies on personal networks and fragmented micro-networks that do not coordinate across regions, resulting in suboptimal matching of worker skills to task requirements. AI-driven platforms overcome this limitation by codifying worker skills and matching them to specific farm requirements. Industry descriptions emphasize that platforms centralize worker information and digitize onboarding processes, enabling better visibility into workforce competencies (El Missaoui, 2026).

The finding that platform adoption explained 23.8% of the variance in labor allocation efficiency suggests that other factors also contribute to efficiency. This is consistent with Guthoff et al. (2026), who found that seasonal labor reallocation patterns are influenced by multiple factors including infrastructure, market access, and institutional contexts. The study area's unique characteristics, including ongoing socio-political challenges, may moderate the platform's effects. However, the results demonstrate that platform adoption represents a significant and statistically meaningful contributor to improved labor allocation efficiency.

Association Between AI-Driven Matching Platform Adoption and Agribusiness Productivity

The finding that platform adoption is positively associated with agribusiness productivity is consistent with theoretical expectations and empirical evidence. Smith (2025) explored how technology and labor regimes intersect in agrifood value chains, highlighting that productivity gains depend on the integration of technological innovation with effective labor organization. AI-driven matching platforms represent such integration, enhancing productivity through improved labor allocation, reduced transaction costs, and optimized deployment of workforce resources.

The observed yield improvements among platform adopters (3.42 tons/ha compared to 2.67 tons/ha for non-adopters) reflect the productivity consequences of timely and skilled labor deployment. Haywood (2024) noted that labor shortages during critical production windows can cause substantial productivity losses, as delays in planting or harvesting directly affect crop yields and quality. By ensuring timely labor availability, platforms prevent such production delays, enabling farmers to optimize production timing. Additionally, the improved skill-task matching ensures that appropriate skills are deployed to appropriate tasks, enhancing operational efficiency and output quality.

The labor productivity finding (2.98 output units per worker-day for adopters versus 2.21 for non-adopters) reflects the efficiency gains from reduced search and coordination costs. Practitioner accounts describe how the current informal recruitment system involves significant transaction costs, including search costs, bargaining costs, and enforcement costs (Merchant, 2024). Industry descriptions similarly note that fragmented processes involving recruiters, paperwork, spreadsheets, and disconnected tools result in productivity losses (El Missaoui, 2026). Platforms reduce these transaction costs by digitizing and centralizing labor management processes, enabling workers to spend more time on productive activities and less on administrative coordination.

The regression analysis revealing labor allocation efficiency as a significant mediator of the platform-productivity relationship supports the theoretical mechanism underpinning this study. The Resource-Based View (Barney, 1991) suggests that effective labor management constitutes a dynamic capability that enables competitive advantage. Platforms enhance this capability by transforming invisible, unstructured labor markets into visible, data-driven ecosystems. The significance of labor allocation efficiency as a predictor of productivity confirms that the platform's value creation occurs through enhanced labor allocation rather than through other mechanisms.

The finding that platform adoption explained 31.2% of the variance in productivity, with labor allocation efficiency accounting for an additional significant portion, suggests that platforms influence productivity through both direct and indirect pathways. This is consistent with the Technology Acceptance Model (Davis, 1989), which suggests that technology adoption leads to performance improvements when users perceive usefulness and ease of use. The substantial explained variance indicates that platform adoption has meaningful practical significance beyond statistical significance.

The findings of this study resonate with broader regional patterns observed in sub-Saharan Africa. Guthoff et al. (2026) found that seasonal labor shifts from farming to off-farm sectors are associated with reduced seasonal food insecurity in Burkina Faso, Malawi, and Uganda. The current study extends this finding by demonstrating that technology-enabled labor allocation improvements are associated with similar positive outcomes within the Cameroonian agricultural context. This suggests that addressing labor allocation constraints through appropriate interventions may generate significant welfare improvements across diverse African agricultural settings.

Girard et al. (2022) examined seasonal work in Senegalese family farming, finding that precarious working conditions constrained livelihoods and asset accumulation. The current study suggests that AI-driven matching platforms may address some of these constraints by formalizing and structuring labor transactions, potentially improving worker conditions through transparency and standardized processes. However, further research is needed to explicitly examine the platform's effects on worker welfare and labor conditions.

The study's findings also align with broader literature on agricultural technology adoption in developing countries. Practitioner accounts emphasize that technological solutions must prioritize accessibility and simplicity, utilizing tools and interfaces familiar to users (Merchant, 2024). The positive association between platform adoption and outcomes in the South-West Region, despite varying levels of digital literacy, suggests that user-centered design principles enhance technology uptake and effectiveness. The high response rate and engagement observed during data collection further suggest potential for technology adoption in the region.

6. Conclusion

This study investigated the association between AI-driven matching platform adoption and seasonal labor allocation efficiency and agribusiness productivity in the South-West Region of Cameroon. The empirical evidence supports both research hypotheses, demonstrating that platform adoption is significantly associated with enhanced labor allocation efficiency and positively associated with agribusiness productivity. Platform adopters exhibited superior performance across all labor allocation indicators, including timeliness of labor availability, skill-task match quality, predictability of labor supply, and satisfaction with recruitment processes. Furthermore, adopters achieved higher crop yields and labor productivity compared to non-adopters.

The findings contribute to the growing body of evidence on digital solutions for agricultural labor challenges in developing countries. The study provides empirical support for the proposition that AI-driven matching platforms are associated with improvements in the coordination failures that characterize informal agricultural labor markets, reducing transaction costs and enabling more efficient deployment of workforce resources. The platform's capacity to create visibility into workforce availability and skills represents a fundamental transformation of labor market functioning, with measurable productivity consequences.

The study also highlights the contextual factors that shape platform effectiveness. While platform adoption demonstrated significant positive associations, the magnitude of these effects varied across enterprises, suggesting that implementation quality, complementary investments, and enterprise characteristics influence outcomes. The study area's unique socio-political context may also moderate platform effectiveness, warranting consideration in future research and program design.

Limitations of the Study

Several limitations should be acknowledged when interpreting the findings of this study. First, the cross-sectional comparative design cannot establish causal relationships between platform adoption and the observed outcomes. The comparison between adopters and non-adopters may be subject to selection bias, as enterprises that chose to adopt platforms may differ systematically from non-adopters in unmeasured ways that also influence labor allocation efficiency and productivity. Factors such as managerial education, access to credit or capital, market linkages, or extension-service contact could jointly drive both platform adoption and better outcomes, but were not measured in this study.

Second, the reliance on self-report Likert measures for key constructs may introduce response bias. While internal consistency reliability statistics (Cronbach's alpha) were acceptable for the composite scales, the measures were newly developed for this study based on conceptual frameworks rather than validated in prior research. Future studies could benefit from using validated instruments or complementing self-report measures with objective productivity data.

Third, the study's single-region, single-country scope limits the generalizability of findings to other contexts. The South-West Region's unique characteristics, including its specific agricultural value chains, socio-political context, and institutional environment, may influence platform effectiveness in ways that differ from other regions or countries. Replication studies in diverse settings would strengthen the evidence base.

Fourth, the study did not examine the mechanisms through which platforms affect outcomes in detail. While the mediating role of labor allocation efficiency was identified, the specific platform features and user behaviors that drive improvements remain unexplored. Qualitative research could provide valuable insights into implementation processes and user experiences.

Implications of the Study

The findings of this study carry several important implications. For agricultural policy, the results suggest that supporting the development and diffusion of AI-driven labor matching platforms could represent a cost-effective strategy for addressing seasonal labor shortages and enhancing agricultural productivity. Policy interventions could include subsidizing platform access for smallholder farmers, investing in digital infrastructure to enable platform functionality, and developing regulatory frameworks that encourage platform development while protecting worker rights.

For agribusiness practitioners, the study demonstrates that platform adoption offers tangible benefits in addressing one of the sector's most persistent challenges. Enterprise managers should consider platform adoption as a strategic investment in labor management capacity, particularly given the significant labor allocation efficiency and productivity gains observed. Training and capacity building to maximize platform utilization could further enhance these benefits.

For platform developers, the study underscores the importance of user-centered design and contextual adaptation. Platforms should be designed to operate effectively within existing technological infrastructures and user capabilities, utilizing familiar interfaces and minimizing required behavioral change. Understanding local labor market dynamics, cultural factors, and institutional constraints is essential for effective platform implementation.

Contribution to knowledge

This study makes several contributions to the scientific literature. First, it provides empirical evidence on AI-driven matching platform effectiveness in an under-researched context, extending the literature beyond developed economies and large emerging markets. The findings contribute to understanding technology adoption and impact in Central African agricultural settings, addressing a significant gap in the existing literature.

Second, the study integrates multiple theoretical perspectives, demonstrating how Transaction Cost Economics, the Resource-Based View, and the Technology Acceptance Model collectively explain platform adoption and impact. This theoretical integration enriches understanding of technology-enabled labor market transformation and provides a framework for future research.

Third, the methodological approach developed for measuring labor allocation efficiency and productivity outcomes, including the reliability testing reported, provides a replicable framework for future studies in similar contexts. The composite indices and measurement instruments developed for this study offer tools for comparative research across regions and time periods.

Recommendations

Based on the finding that platform adoption is significantly associated with enhanced labor allocation efficiency, it is recommended that agribusiness enterprises in the South-West Region prioritize the adoption and effective utilization of AI-driven matching platforms. This entails allocating resources for platform access, investing in staff training to maximize platform functionality, and integrating platform use into core labor management processes. Agricultural extension services and development organizations should support this process by providing technical assistance, facilitating platform access for smallholder enterprises, and building digital literacy among farmers and agricultural workers. Additionally, platform developers should continue to enhance platform features based on user feedback and local contextual requirements, ensuring that platforms remain accessible and responsive to user needs.

Given the demonstrated productivity associations of platform adoption, it is recommended that adopters leverage platform capabilities beyond basic labor matching to achieve broader productivity gains. This includes utilizing platform data analytics to inform strategic labor planning, optimize workforce deployment based on predictive models, and monitor performance indicators for continuous improvement. Enterprises should also consider integrating platform data with other farm management systems to create comprehensive decision support systems. Policy makers should consider incentives for platform adoption, such as tax benefits, subsidized access for smallholders, or inclusion in agricultural support programs. Furthermore, research and development efforts should focus on enhancing platform capabilities for specific crop value chains and agro-ecological zones, ensuring that platforms address the diverse requirements of the region's agricultural sector.

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