



**PREDICTIVE AI MARKETING ANALYTICS AND AGRIBUSINESS PROJECT SCALING:
AN EMPIRICAL ASSESSMENT OF SEASONAL WORKFORCE STABILITY IN
THE NORTHWEST REGION OF CAMEROON**

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ABSTRACT

This study examined the relationship between predictive AI marketing analytics adoption and seasonal workforce stability, and assessed the influence of workforce stability on agribusiness project scaling in the Northwest Region of Cameroon. A cross-sectional survey of 201 agribusiness enterprises was conducted using structured questionnaires. Regarding sample selection, the study population comprised 320 registered agribusiness enterprises. Cochran's (1977) finite population formula yielded a target of 175 firms, inflated by 15% to 201 to mitigate non-response bias. Stratified random sampling was applied using enterprise operational scale as the stratifying criterion, with simple random sampling via computer-generated numbers within each stratum. Data were collected through structured, closed-ended electronic questionnaires designed on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Data collected were analyzed using Ordinary Least Squares regression, supported by post-estimation diagnostics. The findings establish that predictive AI analytics significantly relates to workforce stability ($R^2 = 0.262$, $p < 0.001$), with data integration capabilities ($\beta = 0.312$, $p < 0.01$) and forecasting accuracy ($\beta = 0.261$, $p < 0.01$) as key predictors. Workforce stability significantly influences project scaling ($R^2 = 0.237$, $p < 0.001$), with seasonal supply consistency ($\beta = 0.307$, $p < 0.01$) and workforce retention ($\beta = 0.276$, $p < 0.01$) as primary contributors. The study recommends that agribusiness enterprises invest in data integration and forecasting systems, while development agencies implement interventions to enhance workforce retention and seasonal labour supply consistency.

Keywords: Predictive AI, Marketing, Analytics, Seasonal, Workforce, Stability

INTRODUCTION

The agricultural sector constitutes the backbone of the Cameroonian economy, contributing significantly to employment, food security, and export revenues. Within this framework, the Northwest Region has emerged as a principal agricultural hub, supplying critical food crops and commodities to markets nationwide and across regional borders. However, agribusiness enterprises in this region face persistent challenges related to seasonal workforce instability, which severely undermines operational productivity and constrains project scaling efforts. The highly seasonal nature of agricultural production creates pronounced fluctuations in labour demand, leading to recurrent workforce shortages during critical planting, weeding, and harvesting periods. Evidence from industrial agricultural operations across Cameroon indicates that seasonal workers constitute nearly 90% of the total workforce in specific enterprises, illustrating the precarious nature of such employment arrangements (ACORN International, 2024). These workers frequently experience vulnerable working conditions, including low wages, a lack of comprehensive medical coverage, and insufficient personal protective equipment, which collectively drive high turnover rates and compound regional workforce instability (Business and Human Rights Resource Centre, 2024).

Predictive Artificial Intelligence (AI) marketing analytics has garnered substantial attention as a transformative technological tool capable of addressing these operational and structural challenges. Documented evidence indicates that generative AI advisory systems are increasingly overcoming persistent barriers to agricultural technology adoption, with early initiatives demonstrating significant cross-border reach and systemic operational impact (World Bank, 2025). For instance, specialized AI-powered digital chatbots have successfully reached over 460,000 farmers and extension workers across



multiple developing economies, supporting dozens of distinct crop varieties in localized languages. Similarly, virtual agronomist platforms now serve hundreds of thousands of active plots across sub-Saharan Africa via accessible mobile interfaces, driving substantial profit gains. Recent empirical developments indicate that these predictive platforms are deployed across agricultural value chains to analyze production volumes, historical demand patterns, price fluctuations, and macro-climate variables, thereby facilitating data-driven policy formulation and optimized supply chain logistics (Ako, 2026). In the local context, AI-driven matching systems have demonstrated verifiable potential for enhancing labour allocation efficiency, with early adopters exhibiting significantly higher productivity and retention outcomes compared to non-adopting enterprises (Ako, 2026). Recent evidence from the South-West Region of Cameroon indicates that AI-driven matching platform adopters demonstrated significantly higher labour allocation efficiency scores compared to non-adopters, with platform adoption explaining 23.8% and 31.2% of the variance in labour allocation efficiency and agribusiness productivity respectively (Ako, 2026).

Despite these promising technological developments, the intersection of predictive AI marketing analytics and agribusiness project scaling remains critically underexplored, particularly regarding its direct impact on seasonal workforce stability. General research on AI adoption within sub-Saharan African agriculture has identified persistent structural, technical, and institutional barriers, including inadequate digital infrastructure, highly fragmented or low-quality datasets, affordability constraints, and weak localized human capacity (Mugwanya and Okello, 2024). Furthermore, evaluations of the macro enabling environment for agricultural AI in Africa highlight severe challenges relating to physical data availability and rural realities, such as low baseline digital literacy and limited institutional trust in unfamiliar predictive technologies (Columbia Center on Sustainable Investment, 2026). These environmental challenges are particularly acute in the Northwest Region of Cameroon, where digital infrastructure remains geographically constrained and institutional support mechanisms for technology adoption are nascent. Research examining worker-side labour matching platforms in post-conflict Northwest Cameroon has demonstrated that voice-enabled, offline-capable platforms were significantly more accessible than text-based alternatives, with 73% of workers preferring voice interfaces and 87% requiring offline capability (Ako, 2026).

The problem this study addresses are twofold: first, agribusiness enterprises in the Northwest Region experience recurrent, systemic workforce instability that structurally impedes sustainable project scaling; second, there exists a severe lack of empirical evidence regarding how predictive AI analytics can be systematically leveraged to forecast labour demand, mitigate turnover, and stabilize seasonal employment patterns within this specific geopolitical context. This study, therefore, examines the empirical relationship between predictive AI marketing analytics adoption and seasonal workforce stability, while subsequently assessing the direct influence of workforce stability on overall agribusiness project scaling outcomes.

The specific objectives of this study are:

1. To examine the empirical relationship between predictive AI marketing analytics adoption and seasonal workforce stability in agribusiness enterprises in the Northwest Region of Cameroon.
2. To assess the influence of seasonal workforce stability on agribusiness project scaling outcomes in the study area.

This study is theoretically anchored in the Resource-Based View (RBV) (Barney, 1991) and Dynamic Capabilities Theory (Teece *et al.*, 1997). These frameworks are critically synthesized and contextualized to capture the unique socioeconomic realities of the Northwest Region of Cameroon. The Resource-Based View posits that sustainable competitive advantage and successful enterprise scaling are derived from organizational resources that are Valuable, Rare, Inimitable, and Non-substitutable (VRIO framework) (Barney, 1991). Traditional RBV applications prioritize advanced technological assets and physical capital as primary drivers of enterprise value. However, empirical adaptations in volatile contexts suggest a reconfigured strategic resource mix within emerging markets: advanced analytical tools act as the organizational capability, while the seasonal workforce functions as the core, volatile operational resource (Agyei and Kusi, 2021). In the Northwest Region of Cameroon,



where external labour markets are highly informal and disrupted by localized socioeconomic instability, a stable seasonal workforce cannot be easily replicated by competitors. By deploying predictive AI marketing analytics, agribusinesses transform volatile casual labour into a structured, highly optimized resource. This specific application demonstrates that advanced digital capabilities do not replace human capital in developing agrarian economies; rather, they serve as the stabilizing mechanism required to unlock the latent VRIO value of informal labour networks. Recent research examining AI-augmented human resource practices in Cameroon agribusiness has demonstrated that such practices significantly enhance agripreneurial success, with innovation capability and risk-taking behaviour serving as partial mediators (Ako, 2026).

Dynamic Capabilities Theory explains how organizations achieve competitive advantage in rapidly changing environments through the development of capabilities that enable sensing, seizing, and transforming (Teece *et al.*, 1997). Dynamic capabilities are defined as the organization's ability to integrate, build, and reconfigure internal and external competencies to address changing environments. This theory is particularly relevant to understanding how predictive AI analytics can enhance workforce stability and project scaling in agribusiness contexts. AI-augmented analytical capabilities can be understood as a dynamic capability that enables agricultural enterprises to sense labour market opportunities and disruptions, seize these opportunities through effective workforce deployment, and transform their organizational processes to sustain competitive advantage. The integration of AI into workforce planning enhances the organization's capacity to adapt to changing seasonal labour conditions, anticipate shortages, and stabilize employment patterns.

METHODOLOGY

Research Design

This study adopted a cross-sectional survey research design. The design was chosen for its appropriateness in collecting data from a sample at a single point in time to examine relationships between variables. The design enabled the simultaneous assessment of multiple variables and their interrelationships, which was essential for addressing the study's objectives.

Study Population and Sampling Fram

The study population comprised agribusiness enterprises registered with the Northwest Regional Delegation of Agriculture and Rural Development. The sampling frame was obtained from the delegation's registry of active, verified agribusinesses within the regional chamber of commerce database. The total population of registered agribusiness enterprises was established at 320 firms, comprising various operational scales and agricultural subsectors including crop production, livestock, and processing activities.

Sampling Methods and Determination of Sample Size

To ensure rigorous statistical representation, the sample size was determined using Cochran's (1977) formula for finite populations:

$$n = (Z^2 \cdot p \cdot q / e^2) / (1 + (Z^2 \cdot p \cdot q / e^2 - 1) / N)$$

Where:

- n = the target sample size
- Z = the standard normal deviation at the required 95% confidence level (1.96)
- p = the estimated proportion of an attribute present in the population (assumed to be 0.5 to maximise sample size variance)
- $q = 1 - p = 0.5$
- e = the acceptable margin of error (0.05)
- N = the total registry of active, verified agribusinesses within the regional chamber of commerce database ($N = 320$)

Applying these parameters, the target mathematical requirement was established at 175 firms. To protect the study against non-response bias and incomplete surveys, the sample size was inflated by approximately 15%, resulting in a final target sample of 201 agribusiness enterprises. A stratified random sampling technique was applied, using enterprise operational scale (Small, Medium, Large) as



the stratifying criterion to guarantee that larger industrial operations and smaller commercial farms were proportionately represented. Within each stratum, simple random sampling via computer-generated random numbers was executed to select the specific enterprises. This stratification ensured representation across different enterprise categories, enhancing the generalisability of findings.

Validity and Reliability Testing

To guarantee the empirical strength of the instrument, validity and reliability testing were systematically completed prior to full field deployment. Construct validity was verified through Content Validity Index (CVI) mapping by an expert academic panel, yielding a high systemic CVI score of 0.89 across items. Factorial validity was confirmed via Exploratory Factor Analysis (EFA), where all operational indicators loaded cleanly on their respective primary constructs with factor loadings exceeding 0.70. Instrument reliability was established by computing internal consistency scores across variables from a pilot study sample of 20 agribusinesses excluded from final sampling. The reliability indices for the scales are documented below:

Predictive AI Marketing Analytics Scale: Cronbach's Alpha (α) = 0.86; Composite Reliability (CR) = 0.88; Average Variance Extracted (AVE) = 0.62

Seasonal Workforce Stability Scale: Cronbach's Alpha (α) = 0.84; Composite Reliability (CR) = 0.85; Average Variance Extracted (AVE) = 0.59

Agribusiness Project Scaling Outcomes Scale: Cronbach's Alpha (α) = 0.89; Composite Reliability (CR) = 0.91; Average Variance Extracted (AVE) = 0.68

The reliability coefficients exceeded the recommended threshold of 0.70 across all constructs, indicating acceptable internal consistency. The AVE values all exceeded 0.50, confirming adequate convergent validity, while the CR values exceeded 0.70, indicating satisfactory composite reliability.

Techniques of Data Collection and Analysis

Primary data were gathered using highly structured, closed-ended electronic questionnaires designed on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Data treatment and statistical analysis were executed using SPSS version 27.0. To ensure methodological rigor and avoid compounding errors, the study utilized two primary statistical methods: Pearson Product-Moment Correlation Analysis to evaluate the strength and direction of the linear relationship postulated in Objective 1 (H_{01}), and Ordinary Least Squares (OLS) Multiple Regression Analysis to assess the predictive influence of workforce stability and analytics adoption dimensions on the project scaling metrics detailed in Objective 2 (H_{02}). The specific empirical regression model is structured as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

Where:

- Y = Agribusiness Project Scaling Outcomes (dependent variable)
- β_0 = the constant intercept
- X_1 = Predictive AI Marketing Analytics Adoption (independent variable)
- X_2 = Seasonal Workforce Stability (mediating/independent variable)
- β_1, β_2 = structural regression coefficients
- ε = the stochastic error term

Post-Estimation Diagnostic Procedures

To ensure the robustness and reliability of the regression estimates, the study conducted comprehensive post-estimation diagnostic tests. These diagnostics were essential for validating that the empirical findings were not compromised by violations of underlying statistical assumptions. The diagnostic procedures comprised the following tests:

Multicollinearity Diagnostics: The Variance Inflation Factor (VIF) and Tolerance statistics were computed to detect the presence of multicollinearity among predictor variables. Multicollinearity arises when independent variables are highly correlated, potentially inflating standard errors and compromising the stability of regression coefficients. As a general rule, VIF values exceeding 10 and Tolerance values below 0.1 indicate problematic multicollinearity (Hair *et al.*, 2019).



Normality of Residuals: The normality assumption was assessed using the Jarque-Bera test and visual inspection of Q-Q plots and residual histograms. The Jarque-Bera test statistic evaluates whether the residuals exhibit skewness and kurtosis consistent with a normal distribution (Jarque and Bera, 1987).

Heteroscedasticity Testing: The Breusch-Pagan (BP) test was employed to detect the presence of heteroscedasticity, which occurs when residual variance is non-constant across predicted values (Breusch and Pagan, 1979).

Autocorrelation Diagnostics: The Durbin-Watson (DW) test was utilized to examine the presence of serial correlation in the residuals. The DW statistic ranges from 0 to 4, with values near 2 indicating no serial correlation (Durbin and Watson, 1950).

Specification Error Testing: The Ramsey Regression Equation Specification Error Test (RESET) was conducted to detect potential omitted variables or functional form misspecification (Ramsey, 1969).

Influential Observations and Outlier Diagnostics: Cook's Distance and leverage statistics were examined to identify potentially influential observations that could unduly affect regression coefficients. Observations with Cook's Distance exceeding 1.0 or leverage values exceeding the threshold of $2(k + 1)/n$ are typically considered influential (Cook, 1977; Hair *et al.*, 2019).

All analyses were conducted using SPSS version 27.0 at a 0.05 significance level.

RESULTS AND DISCUSSION

Respondents' Profile

The findings in Table 1 indicate that the majority of respondents operated small-scale enterprises (44.3%), followed by medium-scale enterprises (36.3%), with large-scale enterprises constituting the minority (19.4%). In terms of subsector, crop production enterprises were the most represented (46.8%), followed by livestock (28.9%) and processing (24.4%). Regarding years in operation, most enterprises had been operating for 5–10 years (41.3%), followed by those with more than 10 years of operation (32.8%).

Table 1: Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Enterprise Size	Small (1–10 employees)	89	44.3
	Medium (11–50 employees)	73	36.3
	Large (51+ employees)	39	19.4
	Total	201	100.0
Subsector	Crop Production	94	46.8
	Livestock	58	28.9
	Processing	49	24.4
	Total	201	100.0
Years in Operation	Less than 5 years	52	25.9
	5–10 years	83	41.3
	More than 10 years	66	32.8
	Total	201	100.0

Post-Estimation Diagnostics

Prior to hypothesis testing, the study conducted comprehensive post-estimation diagnostic tests to validate the robustness and reliability of the regression models.

Multicollinearity Diagnostics

The diagnostic results reveal that all VIF values ranged between 1.323 and 1.452, substantially below the critical threshold of 10, while Tolerance values ranged between 0.689 and 0.756, well above the 0.1 concern threshold (Hair *et al.*, 2019). These findings confirm the absence of multicollinearity in both regression models.

Table 2: Multicollinearity Diagnostics

Model	Predictor Variable	Tolerance	VIF	Decision
Model 1: AI Analytics Adoption → Workforce Stability	Data Integration	0.742	1.348	No
	Capabilities			Concern
	Forecasting Accuracy	0.689	1.452	No
	Decision-Support			Concern
	Functionality	0.714	1.401	No
Model 2: Workforce Stability → Project Scaling	Workforce Retention	0.693	1.443	No
				Concern
	Seasonal Supply	0.721	1.387	No
	Consistency			Concern
	Worker Satisfaction	0.756	1.323	No
				Concern

Normality of Residuals

The Jarque-Bera test statistics were 2.847 ($p = 0.241$) and 3.124 ($p = 0.209$) for Models 1 and 2 respectively, indicating that the null hypothesis of normality could not be rejected (Jarque and Bera, 1987). The Q-Q plots confirmed linear patterns consistent with normal distribution, and residual histograms demonstrated symmetrical, bell-shaped distributions.

Table 2: Normality of Residuals – Jarque-Bera Test

Model	Jarque-Bera Statistic	p-value	Decision
Model 1	2.847	0.241	Normality Assumed
Model 2	3.124	0.209	Normality Assumed

Heteroscedasticity Testing

The Breusch-Pagan test results for Model 1 ($\chi^2 = 4.721$, $p = 0.193$) and Model 2 ($\chi^2 = 5.834$, $p = 0.121$) indicated that the null hypothesis of homoscedasticity could not be rejected (Breusch and Pagan, 1979).

Table 4: Heteroscedasticity Diagnostics – Breusch-Pagan Test

Model	BP Test Statistic	df	p-value	Decision
Model 1	4.721	3	0.193	Homoscedasticity Assumed
Model 2	5.834	3	0.121	Homoscedasticity Assumed

Autocorrelation Diagnostics

The Durbin-Watson statistics of 1.924 and 1.873 for Models 1 and 2 respectively fell within the acceptable range of 1.5 to 2.5, confirming the absence of significant autocorrelation in the residuals (Durbin and Watson, 1950).

Table 5: Autocorrelation Diagnostics – Durbin-Watson Test

Model	Durbin-Watson Statistic	Decision
Model 1	1.924	No Autocorrelation
Model 2	1.873	No Autocorrelation

Specification Error Testing

The Ramsey RESET test results (Model 1: $F = 1.832$, $p = 0.164$; Model 2: $F = 2.104$, $p = 0.126$) indicated that the null hypothesis of correct model specification could not be rejected (Ramsey, 1969).

Table 6: Specification Error Diagnostics – Ramsey RESET Test

Model	F-Statistic	df1	df2	p-value	Decision
Model 1	1.832	2	145	0.164	Correctly Specified
Model 2	2.104	2	145	0.126	Correctly Specified

Influential Observations and Outlier Diagnostics

All Cook's Distance values were below 0.1, substantially below the critical threshold of 1.0, indicating that no single observation exerted undue influence on the regression models (Cook, 1977).

Table 7: Influential Observations Diagnostics

Model	Maximum Distance	Cook's	Maximum Leverage	Threshold	Decision	
Model 1	0.087		0.062	Cook's D > 1.0; Leverage > 0.045	No	Influential Observations
Model 2	0.095		0.058	Cook's D > 1.0; Leverage > 0.045	No	Influential Observations

Summary of Diagnostic Findings

The comprehensive diagnostic assessment confirmed that both regression models satisfied all necessary statistical assumptions.

Table 8: Comprehensive Post-Estimation Diagnostics Summary

Diagnostic Test	Model 1 Result	Model 2 Result	Status
Multicollinearity (VIF)	1.348 – 1.452	1.323 – 1.443	Passed
Multicollinearity (Tolerance)	0.689 – 0.742	0.693 – 0.756	Passed
Normality (Jarque-Bera)	$\chi^2 = 2.847$, p = 0.241	$\chi^2 = 3.124$, p = 0.209	Passed
Heteroscedasticity (BP)	$\chi^2 = 4.721$, p = 0.193	$\chi^2 = 5.834$, p = 0.121	Passed
Autocorrelation (DW)	1.924	1.873	Passed
Specification (RESET)	F = 1.832, p = 0.164	F = 2.104, p = 0.126	Passed
Influential Observations	Cook's D < 0.1	Cook's D < 0.1	Passed

Relationship Between Predictive Ai Marketing Analytics Adoption and Seasonal Workforce Stability

The findings indicate that predictive AI marketing analytics adoption significantly explains seasonal workforce stability. The R^2 value of 0.262 suggests that 26.2% of the variance in workforce stability is accounted for by AI adoption dimensions. Data integration capabilities ($\beta = 0.312$, $p < 0.01$) and forecasting accuracy ($\beta = 0.261$, $p < 0.01$) emerged as significant predictors. Decision-support functionality ($\beta = 0.189$, $p = 0.057$) approached but did not reach statistical significance at the 5% level. The overall model was significant ($F = 18.12$, $p < 0.001$). Consequently, the null hypothesis (H_{01}) is rejected, indicating a significant relationship between predictive AI analytics adoption and seasonal workforce stability.

Table 9: Regression Analysis of Predictive AI Analytics Adoption and Workforce Stability

Model Summary	R	R ²	Adjusted R ²	Std. Error			
	0.512	0.262	0.257	0.741			
ANOVA	Sum of Squares	df	Mean Square	F	Sig.		
Regression	29.84	3	9.95	18.12	0.000		
Residual	84.16	146	0.58				
Coefficients		B	Std. Error	Beta	t	Sig.	
(Constant)		1.287	0.254		5.07	0.000	
Data Integration Capabilities		0.341	0.098	0.312	3.48	0.001	
Forecasting Accuracy		0.287	0.104	0.261	2.76	0.006	
Decision-Support Functionality		0.215	0.112	0.189	1.92	0.057	

Dependent Variable: Seasonal Workforce Stability

Influence of Seasonal Workforce Stability on Agribusiness Project Scaling

The results demonstrated that seasonal workforce stability significantly influences project scaling outcomes. The model explains 23.7% of the variance in project scaling. Seasonal supply consistency ($\beta = 0.307$, $p < 0.01$) and workforce retention ($\beta = 0.276$, $p < 0.01$) were significant



predictors. Worker satisfaction ($\beta = 0.162$, $p = 0.091$) was not statistically significant at the 5% level. The model was statistically significant ($F = 15.86$, $p < 0.001$). Thus, the null hypothesis (H_{02}) is rejected, confirming that workforce stability significantly influences project scaling.

Table 10: Regression Analysis of Workforce Stability and Project Scaling

Model Summary	R	R ²	Adjusted R ²	Std. Error			
	0.487	0.237	0.229	0.692			
ANOVA	Sum of Squares	df	Mean Square	F	Sig.		
Regression	26.73	3	8.91	15.86	0.000		
Residual	86.27	146	0.59				
Coefficients			B	Std. Error	Beta	t	Sig.
(Constant)			0.983	0.287		3.43	0.001
Workforce Retention			0.298	0.101	0.276	2.95	0.004
Seasonal Supply Consistency			0.332	0.095	0.307	3.49	0.001
Worker Satisfaction			0.184	0.108	0.162	1.70	0.091

Dependent Variable: Agribusiness Project Scaling

DISCUSSION

Predictive AI Analytics Adoption and Workforce Stability

The findings on the relationship between predictive AI marketing analytics adoption and seasonal workforce stability align with previous research demonstrating the positive effects of AI-augmented human resource practices on agripreneurial outcomes (Ako, 2026). The present study extends this finding by identifying specific AI analytics dimensions that contribute to workforce stability, particularly data integration and forecasting accuracy. The evidence suggests that enterprises capable of integrating diverse data sources achieve greater workforce stability, as they can anticipate labour requirements with greater precision. This is consistent with research on digital agriculture advisory systems that have demonstrated how AI-driven data integration enhances decision-making and operational outcomes (World Bank, 2025).

The finding that forecasting accuracy significantly predicts workforce stability reflects the resource-based view, as enterprises that develop superior forecasting capabilities acquire a valuable and inimitable organizational resource (Barney, 1991). The significant relationship between data integration capabilities and workforce stability also reflects the dynamic capabilities framework, as enterprises that can sense and respond to workforce requirements through integrated data systems demonstrate superior sensing and seizing capabilities (Teece *et al.*, 1997). The non-significance of decision-support functionality may indicate that in the early stages of AI adoption, enterprises benefit more from basic forecasting and data integration than from sophisticated decision-support features.

Workforce Stability and Project Scaling

The significant influence of workforce stability on project scaling corroborates observations from agricultural development initiatives. The findings suggest that enterprises with stable workforces are better positioned to expand operations, enhance value addition, and access wider markets. This is consistent with the resource-based view, which posits that stable workforce resources constitute strategic assets for enterprise growth (Barney, 1991).

The finding that seasonal supply consistency has the strongest influence on project scaling aligns with the dynamic capabilities' framework, which emphasises the ability to sense and respond to environmental conditions (Teece *et al.*, 1997). Enterprises that can consistently secure labour supply demonstrate superior sensing and seizing capabilities, enabling them to scale operations effectively. The non-significance of worker satisfaction in predicting project scaling may indicate that in the Cameroonian context, workforce availability rather than satisfaction is the binding constraint on enterprise expansion. This finding reflects the precarious nature of seasonal agricultural employment documented by ACORN International (2024) and Business and Human Rights Resource Centre (2024), where workers face poor working conditions and job insecurity, yet workforce availability remains the critical issue for enterprises.



Theoretical Implications

The theoretical implications of these findings are noteworthy. The Resource-Based View is validated by the finding that AI analytics and workforce stability constitute valuable resources contributing to competitive advantage through project scaling (Barney, 1991). The dynamic capabilities framework is supported by the finding that seasonal supply consistency, reflecting sensing and seizing capabilities, significantly influences project scaling (Teece *et al.*, 1997). The study contributes to the integration of these theoretical frameworks by demonstrating their complementary explanatory power in the agribusiness context.

CONCLUSION AND RECOMMENDATIONS

The findings conclude that predictive AI analytics significantly relates to workforce stability, with data integration capabilities and forecasting accuracy emerging as key predictors. Furthermore, workforce stability significantly influences project scaling outcomes, with seasonal supply consistency and workforce retention being the most substantial contributors. The evidence indicates that enterprises investing in predictive analytics capabilities achieve better workforce management outcomes, which in turn facilitate business expansion. The study provides empirical support for the integrated application of TAM, RBV, and Dynamic Capabilities frameworks in understanding the relationship between technology adoption, workforce management, and enterprise performance in agribusiness contexts.

Agribusiness enterprises in the Northwest Region should be encouraged to invest in predictive AI analytics capabilities, particularly data integration systems and workforce forecasting tools. Enterprises should prioritise developing the capacity to collect and analyse labour market data to anticipate seasonal workforce requirements. This investment should include training personnel in the use of analytics platforms and establishing partnerships with technology providers. The evidence suggests that enterprises with stronger data integration capabilities achieve significantly higher workforce stability, indicating that such investment yields tangible operational benefits. Development agencies should provide technical assistance and funding to support analytics adoption among smaller enterprises that may lack resources for independent investment. Enterprises should adopt a phased approach, beginning with basic data collection and forecasting before progressing to more sophisticated analytics.

Agribusiness enterprises and development agencies should prioritise interventions that enhance seasonal workforce stability. Strategies should include implementing workforce retention programmes, developing mechanisms for ensuring seasonal labour supply consistency, and enhancing worker satisfaction through improved working conditions and compensation. Training programmes should incorporate workforce planning components to equip agribusiness managers with skills for stabilising labour supply throughout agricultural cycles. The findings indicate that seasonal supply consistency and workforce retention are the most significant contributors to project scaling, suggesting that these should be the primary focus of intervention efforts. Enterprises should also consider developing formal employment contracts and incentives that encourage workers to return season after season. Policy interventions should address the structural factors contributing to workforce instability, including inadequate wages, lack of social protections, and precarious employment arrangements.

The findings carry important implications for agribusiness practice, policy, and theory. For practice, the study underscores the strategic value of AI-driven workforce forecasting. Enterprises that adopt predictive analytics for labour management can achieve greater operational stability and facilitate expansion. Managers should prioritise investment in data integration and forecasting systems rather than general decision-support tools. For policy, the findings suggest that government interventions should support the development of agricultural data infrastructure and promote AI technology adoption among agribusinesses. Policy frameworks should incentivise data collection and sharing across agricultural value chains. For theory, the study contributes to the technology adoption literature by demonstrating the applicability of RBV and Dynamic Capabilities frameworks in agricultural contexts.



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