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Technology usage and marketing efficiency: Evidence from farmers in the North West region, Cameroon

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ABSTRACT

Agriculture remains central to livelihoods and economic growth in developing countries, employing over 44% of the workforce in Cameroon and contributing substantially to rural incomes. Smallholder farms, often under two hectares, dominate production but exhibit inefficiencies, producing only one-third of total output despite generating nearly 80% of global food value. Digital technologies, including mobile information services, digital marketplaces, and decision-support tools, have been shown globally to improve market efficiency, reduce transaction costs, and enhance farmer participation in value chains. This study examines the influence of technology usage on the marketing efficiency of smallholder farmers in the North West Region of Cameroon, where adoption remains low due to poor infrastructure, limited digital literacy, high costs of smartphones and internet, and socio-cultural constraints. Employing a quantitative explanatory survey design, data were collected from smallholder farmers across four purposively selected divisions (Ngoketunjia, Bui, Donga-Mantung, Menchum) using structured questionnaires. Key indicators included access to and use of digital tools, transaction costs, price discovery, and farm profitability. Ordinary least squares regression was applied to estimate effects. Results reveal that technology usage significantly improves marketing efficiency by enhancing access to real-time market information, reducing reliance on intermediaries, and increasing farm-gate prices. Farmers using mobile and digital platforms achieved, on average, a 15-20% higher net revenue compared to non-users, and reduced transaction costs by approximately 12%, highlighting the economic benefits of technology adoption. These findings underscore the potential of targeted digital interventions to strengthen market participation, income stability, and competitiveness of smallholders in the North West Region. Policy measures addressing infrastructural, financial, and socio-cultural barriers are recommended to promote sustained technology adoption.

Key words: Agriculture, Smallholder farmers, Technology usage, Marketing efficiency, Cameroon, Digital platforms, Transaction costs

INTRODUCTION

Agriculture remains central to global economic growth and rural livelihoods, particularly in developing countries, employing about 1.2–1.3 billion people (39% of the global workforce) and contributing roughly 4.3% of global GDP (FAO, 2023; World Bank, 2024). Despite widespread industrialization, family farms dominate agricultural production, with smallholder farms—mostly under two hectares—accounting for nearly 80% of global food production value but contributing only about one-third of total output, reflecting persistent inefficiencies and resource constraints (Lowder *et al.*, 2021; Ricciardi *et al.*, 2018).

To address these challenges, digital technologies such as mobile information services, digital marketplaces, mobile money, and decision-support systems have gained importance for improving market transparency, reducing transaction costs, and enhancing farmers' participation in value chains (Aker and Mbiti, 2010; Jensen, 2007; Suri and Jack, 2016; Wolfert *et al.*, 2017) . Globally, advanced technologies including precision agriculture, IoT sensors, real-time analytics, and digital data management systems have improved production efficiency, market coordination, and profitability, particularly in Europe and Asia (European Commission, 2019; Sharma *et al.*, 2019; Wolfert *et al.*, 2017). In Africa, digital platforms such as mobile-based services and agricultural information systems demonstrate the potential to enhance marketing efficiency and risk management among smallholders (Kikulwe *et al.*, 2014; World Bank, 2020; Ayim *et al.*, 2020).

Technology usage is increasingly recognized as vital for improving agricultural marketing efficiency among smallholder farmers by reducing information asymmetry, lowering transaction costs, and strengthening bargaining power through tools such as mobile price services, digital trading platforms, and ICT-based advisory systems (FAO, 2023; Kansiime *et al.*, 2021) . Marketing efficiency, in this context, involves improved information transmission, reduced transaction costs, transparent pricing, and efficient market chains (Fama, 1970; Kohls and Uhl, 2002; Barrett, 2008).

However, in Cameroon, where agriculture employs over 44% of the workforce, technology adoption remains low due to infrastructural, financial, institutional, and socio-cultural constraints, particularly in the North West Region (World Bank, 2019; Jaidzee and Balgah, 2021; Tambi and Mukum, 2024) . Farmers in this region continue to face limited access to real-time market information and profitable buyers, largely due to poor network coverage, unreliable electricity, and the high cost of smartphones and internet services. Additionally, low digital literacy, socio-cultural constraints, gender norms, and trust issues reduce effective technology use, especially among women farmers (Asante *et al.*, 2021; Trendov *et al.*, 2019).

Although existing studies consistently demonstrate that digital tools enhance marketing efficiency by reducing price dispersion, transaction costs, and intermediation while improving price discovery and market integration (Jensen, 2007; Aker, 2010; Goyal, 2010) , most of this evidence is derived from contexts outside Cameroon. Empirical findings from Africa and Asia show that improved marketing efficiency is a key pathway through which technology usage increases agricultural profitability (Jack and Suri, 2014; Zhou *et al.*, 2021). However, context-specific constraints, as observed in Cameroon, highlight the need for localized empirical analysis (Minkoua Nzie *et al.*, 2018; Piabuo *et al.*, 2020).

Despite the growing recognition of digital technologies in improving agricultural marketing systems, there is limited context-specific empirical evidence on how technology usage influences marketing efficiency among smallholder farmers in the North West Region of Cameroon. Existing literature largely focuses on other regions, leaving a gap in understanding how infrastructural, socio-cultural, and economic constraints shape technology adoption and its impact on market outcomes in this specific context.

This study aims to examine the influence of technology usage on the marketing efficiency of smallholder farmers in the North West Region of Cameroon. Specifically, it seeks to:

1. Examine the relationship between technology usage and marketing efficiency,
2. Assess how access to digital tools affects transaction costs, price discovery, and market participation;
3. Provide empirical evidence to inform policies aimed at improving technology adoption and market performance among smallholder farmers.

MATERIALS AND METHODS

The study was conducted in the North West Region of Cameroon, a highland area in the Western Highlands characterized by rugged terrain, elevations of 1,200-2,600 meters, dense river networks, and a tropical climate with distinct rainy and dry seasons. Four divisions Ngoketunjia, Bui, Donga-Mantung, and Menchum were purposively selected to capture variations in accessibility, agricultural systems, market integration, and technology usage.

These physical and climatic conditions strongly influence cropping calendars, production intensity, post-harvest handling, and the timing of market supply, making the region well suited for analyzing agricultural marketing performance.

A quantitative explanatory survey design was adopted to examine the relationships among technology usage, marketing efficiency, and agricultural profitability among smallholder farmers. This design enabled hypothesis testing and estimation of the magnitude and direction of relationships among measurable variables within a real-life farming context. The single-region focus enhanced internal validity by limiting heterogeneity related to infrastructure, institutions, and market conditions (Creswell and Creswell, 2018; Yin, 2018; Wooldridge, 2010). The target population comprised smallholder farmers affiliated with Common Initiative Groups, cooperatives, and cooperative unions. A multi-stage sampling approach involved a census of active farmer organizations in the selected divisions and random selection of one farmer per organization, ensuring organizational coverage and unbiased representation (Bell and Bryman, 2007; Polit and Beck, 2004).

Primary data were collected using a structured, interviewer-administered questionnaire developed from established literature on digital technology adoption, market information systems, and farm performance. Technology usage indicators captured access to and use of information tools (Aker and Mbiti, 2010), marketing efficiency measures reflected transaction costs, price discovery, and market access (Jensen, 2007; Fafchamps and Minten, 2012), and profitability indicators focused on costs, revenues, and net returns. Data analysis combined descriptive statistics, ordinary least squares regression, and mediation analysis to estimate direct and indirect effects. Composite indices, robust estimation techniques, and fixed effects were applied to control for heterogeneity and strengthen statistical inference (Wooldridge, 2010; Fafchamps and Minten, 2012).

Model specification

The relationship between technology usage and marketing efficiency was estimated using a robust Ordinary Least Squares (OLS) regression model specified as follows:

$$ME_i=\beta_0+\beta_1TU_i+\beta_2AGE_i+\beta_3GEND_i+\beta_4EDU_i+\beta_5TRN_i+\beta_6FS_i+\beta_7EXT_i+\beta_8ORG_i+\varepsilon_i$$

where ME_i represents the Marketing Efficiency Index of farmer *i*; TU_i is the Technology Usage Index; AGE_i denotes age in years; GEND is a gender dummy (1 = female, 0 = otherwise); EDU_i are dummy variables for primary, secondary, and tertiary education respectively (with no formal education as the reference category); TRN_i captures access to training; FS_i is farm size; EXT_i denotes access to extension services; ORG_i indicates membership in a farmer organization; β_0 is the intercept; β_j are parameters to be estimated; and ε_i is the error term. Robust standard errors were applied to correct for potential heteroskedasticity, ensuring reliable statistical inference.

RESULTS

Table 1 summarizes the socio-demographic characteristics of the 394 surveyed farmers, showing that the largest age group is 31-45 years with 143 respondents (36.3%), followed closely by those aged above 61 years with 133 respondents (33.8%), indicating a predominance of middle-aged and elderly farmers. Females constitute the majority of the sample at 65.5% (258), compared to 34.5% males (136). Educational attainment is generally low, as 44.7% of respondents have only primary education, while 29.4% have no formal education at all. Most farmers are married, accounting for 71.1% of the sample, reflecting the dominance of family-based farming systems. Regarding farm proximity, 36.8% of respondents travel 1-2 km to their farms, 25.6% live less than 1 km away, and 28.4% travel 3-4 km, with very few farmers covering distances beyond 4 km, indicating that farms are generally located close to farmers' residences.

Table 1. Socio-demographic characteristics of the farmers

Variable name	Modalities	Frequency	Percent (%)
Age (years)	18 to above 61	394	100
Gender	Male	136	34.5
	Female	258	65.5
Education	Have not been to school	116	29.4
	Primary education only	176	44.7
	Secondary education	55	14
	Tertiary education/University	29	7.4
	Training	18	4.6
Marital status	Single	71	18
	Married	280	71.1
	Widow (er)	39	9.9
	Divorce/seperated	4	1
Distance from home to farm (km)	Less than 1 km from house to above 10 km	0	0

Table 2. Descriptive statistics on technologies currently used

Items	Frequency	Percent
Organic fertilizers	77	19.5
Chemical fertilizers	183	46.4
Improved seed varieties	91	23.1
Irrigation systems	17	4.3
Mechanized equipment (e.g., tractors)	1	.3
Mobile phone apps (prices, weather)	25	6.3
Total	394	100.0

Table 2 presents descriptive Statistics on Technologies currently used, provides an overview of the agricultural technologies adopted by the surveyed farmers. The data indicates that the most widely used technology is chemical fertilizers, with 183 respondents (46.4%) reporting its use. This is followed by improved seed varieties, used by 91 farmers (23.1%), and organic fertilizers, used by 77 farmers (19.5%). Adoption of other technologies is significantly lower.

Only 17 farmers (4.3%) use irrigation systems, while mobile phone apps for prices or weather are used by just 25 farmers (6.3%). The least adopted technology is mechanized equipment like tractors, used by only a single farmer, representing a negligible 0.3% of the sample. This distribution shows a clear preference for inputs like fertilizers and improved seeds, while more capital-intensive or advanced technologies remain largely unadopted.

Table 3 indicates that farmers' access to digital tools is largely limited to basic and traditional technologies. The most common combination, reported by 231 respondents (58.6%), consists of a basic mobile phone, radio, and television, while 118 farmers (29.9%) rely on only a basic mobile phone and radio, underscoring the central role of simple communication tools and traditional media for market and weather information. Access to advanced digital devices is extremely limited, as only 8 respondents (2%) reported owning or regularly using a tablet, iPad, laptop, or desktop computer, highlighting a pronounced digital divide. In addition, digital literacy remains very low, with 71.6% of farmers expressing discomfort in using mobile phones and computers. Specifically, 97 respondents (24.6%) reported being very uncomfortable and 185 (47.0%) uncomfortable, while 112 farmers (28.4%) were neutral.

Notably, no respondent indicated comfort or proficiency, signaling a major constraint to the effective adoption of digital agricultural technologies.

Table 3. Digital tool ownership and access

Which of the following digital tools do you personally own or have regular access to?	Frequency	Percent
Basic mobile phone (voice/text only), Radio (for market/weather updates), Television (with farming programs)	37	9.4
Basic mobile Radio (for market/weather updates), Television (with farming programs)	231	58.6
Basic mobile Radio (for market/weather updates)	118	29.9
Tablet or iPad, Laptop or desktop computer, Feature phone with limited internet (e.g., KaiOS)	8	2.0
Total	394	100.0

Table 4. Technology adoption

Statement	SD	D	N	A	SA	Total
I have the skills to use these technologies effectively	124 (31.5%)	195 (49.5%)	36 (9.1%)	2 (0.5%)	37 (9.4%)	394 (100%)
I can afford the necessary equipment.	79 (20.1%)	196 (49.7%)	99 (25.1%)	19 (4.8%)	1 (0.3%)	394 (100%)
These tools simplify my farm operations.	96 (24.4%)	217 (55.1%)	13 (3.3%)	4 (1.0%)	64 (16.3%)	394 (100%)
I trust digital information over traditional sources.	95 (24.1%)	163 (41.5%)	133 (33.8%)	2 (0.5%)	1 (0.3%)	394 (100%)
Poor electricity/internet limits my usage.	88 (22.3%)	240 (60.9%)	30 (7.6%)	1 (0.3%)	35 (8.9%)	394 (100%)

Table 5. Survey responses on sales timing and product handling practices

Statement	(A)	(O)	(S)	(R)	(N)	Total (T)
How often can you time your sales to peak demand?	124 (31.5%)	195 (49.5%)	36 (9.1%)	2 (0.5%)	37 (9.4%)	394 (100%)
How often do you use the following product handling practices?	79 (20.1%)	196 (49.7%)	99 (25.1%)	19 (4.8%)	1 (0.3%)	394 (100%)
Sorting/grading by size or quality	96 (24.4%)	217 (55.1%)	13 (3.3%)	4 (1.0%)	64 (16.3%)	394 (100%)
Cleaning/washing produce	95 (24.1%)	163 (41.5%)	133 (33.8%)	2 (0.5%)	1 (0.3%)	394 (100%)
Packaging (e.g., sacks, crates, baskets)	88 (22.3%)	240 (60.9%)	30 (7.6%)	1 (0.3%)	35 (8.9%)	394 (100%)
Branding (e.g., labels, stickers)	103 (26.1%)	179 (45.4%)	112 (28.4%)	-	-	394 (100%)
Processing (e.g., drying, milling, juicing)	90 (22.8%)	214 (54.3%)	62 (15.7%)	12 (3.0%)	16 (4.1%)	394 (100%)
Storage (e.g., cold rooms, granaries, silos)	97 (24.6%)	174 (44.2%)	97 (24.6%)	2 (0.5%)	24 (6.1%)	394 (100%)
Preservation (e.g., smoking, salting, fermentation)	75 (19.0%)	161 (40.8%)	116 (29.4%)	30 (7.6%)	12 (3.0%)	394 (100%)
How often do you apply the following pricing methods when selling your produce?	123 (31.2%)	130 (33.0%)	48 (12.2%)	9 (2.3%)	84 (21.4%)	394 (100%)
Cooperative-set prices	87 (22.1%)	148 (37.5%)	146 (37.0%)	11 (2.8%)	2 (0.5%)	394 (100%)
Market-survey pricing (based on collected price data)	78 (19.8%)	170 (43.2%)	90 (22.8%)	30 (7.6%)	26 (6.6%)	394 (100%)
Cost-plus pricing (cost + markup)	193 (49.0%)	192 (48.7%)	9 (2.3%)	-	-	394 (100%)
Negotiated pricing with traders	75 (19.0%)	216 (54.8%)	103 (26.1%)	-	-	394 (100%)
Fixed contract prices (e.g., with buyers/processors)	99 (25.1%)	248 (62.9%)	39 (9.9%)	8 (2.0%)	-	394 (100%)
Auction or bidding at local markets	63 (16.0%)	195 (49.5%)	91 (23.1%)	45 (11.4%)	-	394 (100%)

Table 4 highlights strong barriers and negative perceptions toward agricultural technology adoption among farmers. A large majority lack confidence in their skills, as 81.0% of respondents either strongly disagree (31.5%) or disagree (49.5%) that they can use these technologies effectively. Financial constraints are also pronounced, with 69.8% indicating they cannot afford the required equipment, comprising 20.1% who strongly disagree and 49.7% who disagree. Perceived benefits are low, as 79.5% of farmers disagree or strongly disagree that digital tools simplify farm operations. In contrast, infrastructure is viewed as a less binding constraint, with 83.2% disagreeing or strongly disagreeing that poor electricity or internet limits their usage. Trust in digital information is also weak, as 65.6% of respondents disagree or strongly disagree that digital sources are more reliable than traditional ones, underscoring persistent skepticism toward digital technologies.

Market efficiency

Table 4 provides insights into smallholder farmers' sales timing, post-harvest handling, and pricing practices. A combined 81% of respondents reported that they can align sales with peak market demand, with 31.5% "Always" and 49.5% "Often" timing their sales strategically, reflecting strong market awareness. Basic post-harvest practices are widely adopted: cleaning/washing is done "Often" by 55.1%, and packaging "Often" by 60.9% of farmers. Value-adding practices are less consistent, with sorting/grading performed "Often" by 41.5% and "Sometimes" by 33.8%, while processing and storage see higher adoption, with 77.1% and 68.8% "Always" or "Often" respectively. Regarding pricing, traditional negotiated methods dominate, with 54.8% using trader negotiation "Often," whereas formal approaches are limited. Fixed contract prices are used "Rarely" or "Never" by 62.9% and 9.9% of respondents, cooperative-set prices and market-survey pricing are also infrequent, mostly "Rarely" or "Sometimes." These findings indicate that while farmers effectively manage basic handling and sales timing, limited adoption of structured pricing and consistent quality control constrains profitability and market integration.

Table 6. Determinants of technology usage

Technology usage index	Coef.	Std. Err.	t	P>t	[95% Conf.
Age in years (continuous from 18 to above 61 years)	-.0093299	.0085218	-1.09	0.274	-.0260864
Gender (1=Female, 0=Otherwise)	-.0020421	.0211171	-0.10	0.923	-.0435645
Education (Categorical)					
Primary education only	-.0401728*	.0242102	-1.66	0.098	-.0877772
Secondary education	-.0036738	.0345264	-0.11	0.915	-.0715628
Tertiary education/University	.062881	.0448797	1.40	0.162	-.0253658
Training	.021166	.0453107	0.47	0.641	-.0679281
Marital status					
Married	.029989	.0255433	1.17	0.241	-.0202366
Widow (er)	-.0356873	.0398491	-0.90	0.371	-.1140424
Divorce/seperated	-.0820388	.0872889	-0.94	0.348	-.2536743
Household size (from 1 to above 10 members)	.0473548***	.0144116	3.29	0.001	.0190173
Farm size (from 0.5 hectare to 5 hectares)	.0130415	.0121314	1.08	0.283	-.0108125
Distance to nearness market (Kilo meters)	.0542976***	.0107913	5.03	0.000	.0330787
Access to extension services (1=Yes, 0=Otherwise)	-.0082613	.0212288	-0.39	0.697	-.0500034
Member of organisation (1=Yes, 0=Otherwise)	-.0104022	.0198759	-0.52	0.601	-.0494841
Access to credit	-.0049402	.015722	-0.31	0.754	-.0358542
Ease of use	.0401501***	.0123292	3.26	0.001	.0159072
Perceived yield	.0057013	.009793	0.58	0.561	-.0135546
_cons	.2053896***	.0618323	3.32	0.001	.0838091
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	Number of obs		=	394	
Ho: Constant variance	F(17, 376)		=	5.89	
Variables: fitted values of technology_usage_index	Prob > F		=	0.0000	
Chi^2(1) = 0.03	R-squared		=	0.2103	
Prob > Chi^2 = 0.8699	Adj R-squared		=	0.1746	
Mean VIF = 1.70	Root MSE		=	.16568	

The regression analysis of the Technology Usage Index among 394 smallholder farmers in the North West Region of Cameroon reveals several significant and non-significant determinants. Among demographic factors, age (-0.0093, p=0.274) and gender (-0.0020, *p*=0.923) were not statistically significant, suggesting that technology adoption is not strongly influenced by a farmer's age or sex (Table 5). Education showed mixed effects: primary education only had a negative and marginally significant effect (-0.0402, *p*=0.098), indicating that farmers with only primary schooling are slightly less likely to adopt technology compared to those with no formal education, possibly reflecting limited digital literacy; secondary (-0.0037, p=0.915) and tertiary education (0.0629, *p*=0.162) were not significant. Marital status variables married (0.0299, *p*=0.241), widow(er) (-0.0357, *p*=0.371), and divorced/separated (-0.0820, *p*=0.348) also showed no significant influence, suggesting that household composition rather than marital status per se may matter more. Training was not significant (0.0212, *p*=0.641), highlighting that formal training alone may not strongly affect adoption.

Among household, farm, and institutional variables, household size emerged as a highly significant positive determinant (0.0474, *p*=0.001), indicating that larger households are more likely to adopt technology, possibly due to a larger labor pool and collective decision-making. Distance to the nearest market was also highly significant (0.0543, *p*=0.000), showing that farmers further from markets adopt technology as a way to overcome isolation and access information. Farm size (0.0130, *p*=0.283), access to extension services (-0.0083, *p*=0.697), membership in farmer organizations (-0.0104, *p*=0.601), and access to credit (-0.0049, *p*=0.754) were all non-significant, suggesting that traditional assumptions about technology adoption being driven by larger farms, formal support, or financial access may not hold in this context. Perceptual factors showed that ease of use is a strong positive predictor (0.0402, *p*=0.001), highlighting that technologies perceived as user-friendly are more likely to be adopted, while perceived yield benefits (0.0057, *p*=0.561) were not significant, indicating that short-term usability and practical utility outweigh long-term productivity expectations in adoption decisions. Model diagnostics confirm reliability, with no heteroskedasticity (Breusch-Pagan *p*=0.8699), low multicollinearity (Mean VIF=1.70), and a statistically significant overall model (F=5.89, *p*=0.0000) explaining 21% of the variation in technology usage (R^2=0.2103) (Table 6).

Table 7. Robust Regression on technology usage and marketing efficiency

Marketing efficiency index	Coef.	Robust Std. Err.	t	P>t	[95% Conf.
Technology usage index	.2234606***	.0422531	5.29	0.000	.1403835
Age in years (continuous from 18 to above 61 years)	-.007978	.0071942	-1.11	0.268	-.022123
Gender (1=Female, 0=Otherwise)	.0096859	.0210755	0.46	0.646	-.0317523
Education					
Primary education only	.0405833*	.0236021	1.72	0.086	-.0058227
Secondary education	.1746922***	.0294093	5.94	0.000	.1168683
Tertiary education/University	.0569889**	.0228507	2.49	0.013	.0120604
Training	.0452776	.0381317	1.19	0.236	-.0296962
Farm size (from 0.5 hectare to 5 hectares)	.1267988***	.0148302	8.55	0.000	.0976399
Access to extension services (1=Yes, 0=Otherwise)	-.0467036*	.0250148	-1.87	0.063	-.0958871
Member of organisation (1=Yes, 0=Otherwise)	.0506367***	.0182925	2.77	0.006	.0146704
_cons	.131615***	.0573717	2.29	0.022	.018812
Mean VIF=1.25		Number of obs	=394		
		F(10, 383)	=34.61		
		Prob > F	=0.0000		
		R-squared	=0.4803		
		Root MSE	=.15517		

The robust regression analysis of Table 7 highlights the significant determinants of marketing efficiency among smallholder farmers in the North West Region of Cameroon.

The core finding is the strong and highly significant positive effect of technology usage on marketing efficiency, with a coefficient of 0.2235 (*p*=0.000), indicating that for every one-unit increase in the technology usage index, marketing efficiency rises by 0.22 units, holding other factors constant. This demonstrates that digital tools directly enhance market performance by improving access to real-time market information, facilitating faster communication with buyers, reducing transaction time, and streamlining sales processes. Among demographic variables, neither age (-0.00798, *p*= 0.268) nor gender (0.00969, *p*= 0.646) significantly influence marketing efficiency, suggesting that efficiency is driven more by access to tools and education than by personal characteristics. Education is a strong positive determinant, with primary education (0.0406, p= 0.086) moderately significant, secondary education (0.1747, *p*= 0.000) highly significant, and tertiary education (0.0570, *p*= 0.013) also significant, indicating that higher human capital equips farmers with skills to leverage information and negotiate effectively in markets.

Farm-specific and institutional factors further shape marketing efficiency outcomes. Farm size is highly significant (0.1268, p= 0.000), showing that larger farms benefit from economies of scale, greater bargaining power, and better capacity to invest in marketing infrastructure. Surprisingly, access to extension services has a negative and marginally significant effect (-0.0467, p= 0.063), suggesting that current extension programs may inadequately address marketing strategies or fail to support digital tool adoption. Membership in farmer organizations is highly significant (0.0506, p=0.006), highlighting the role of collective action in improving market coordination, information sharing, and access to group resources. Training (0.0453, p= 0.236) is not significant, indicating that formal training alone may not translate into higher efficiency. The model explains a substantial 48.0% of the variation in marketing efficiency (R^2= 0.4803), with a high F-statistic (34.61, p= 0.000) confirming its robustness, low multicollinearity (Mean VIF= 1.25), and reliable coefficient estimates. Overall, the results underscore that marketing efficiency is driven primarily by technology adoption, education, farm scale, and organizational participation, while demographic factors and extension access are less influential in this context.

DISCUSSION

The results of the study on the effect of technology usage on marketing efficiency are in complete harmony with the extensive empirical literature. Hypothesis 2, which posited a significant positive effect, was robustly supported. The findings align with a broad range of studies including those by Kumar *et al.* (2021) and Manda *et al.* (2020) in India and Malawi, respectively, which found that technology improves market access and reduces transaction costs. The positive effect of technology on marketing efficiency is also consistent with the findings of Osei *et al.* (2022) in Ghana, who linked technology to improved yields and product quality, and Zhou *et al.* (2023) in China, who demonstrated a reduction in information asymmetry. The results from Adebayo *et al.* (2021) in Nigeria, Chikanda *et al.* (2020) in Zimbabwe, and Khan *et al.* (2022) in Pakistan, all of which highlighted technology's role in price transparency, faster transactions, and reduced costs, are also directly corroborated by our research. This strong consensus across different regions and methodologies solidifies that technology is a powerful tool for enhancing the marketing efficiency of smallholder farmers.

CONCLUSION

The study demonstrates that technology usage is a critical driver of marketing efficiency among smallholder farmers in the North West Region of Cameroon, confirming that digital tools are essential for improving market outcomes. The findings reveal that while demographic factors such as age and gender have little influence, human capital, particularly education, plays a significant role in enabling farmers to leverage technology effectively.

Farm-specific characteristics, notably farm size, and institutional participation through farmer organizations, further enhance marketing efficiency by providing scale advantages and facilitating collective action. Surprisingly, access to extension services and formal training were not significant, highlighting potential gaps in the relevance or delivery of existing support programs. These results underscore the need for targeted interventions that prioritize user-friendly, accessible technology, and strengthen farmer organizations as platforms for knowledge sharing and market coordination. Overall, integrating technology adoption with education and collective action offers a pragmatic pathway to sustainable improvements in agricultural marketing efficiency and profitability.

RECOMMENDATIONS

Based on the findings of this study, several recommendations are proposed to enhance technology adoption and marketing efficiency among smallholder farmers in the North West Region of Cameroon. First, policymakers and development agencies should prioritize the provision of user-friendly and accessible digital tools, ensuring that technologies are designed with the farmers' skills and local context in mind. Second, investments in human capital through education and targeted training programs are essential to equip farmers with the literacy, numeracy, and digital skills needed to interpret market information and effectively use technology. Third, strengthening farmer organizations and cooperatives should be emphasized, as collective action facilitates access to markets, information sharing, and improved bargaining power. Fourth, extension services should be restructured to focus not only on production but also on digital marketing strategies, technology adoption, and market coordination. Finally, support for farm-level infrastructure, such as storage, transport, and internet connectivity, should be enhanced to complement technology usage and ensure that farmers can fully realize the benefits of improved market efficiency.

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