An Econometric Analysis of the Impact of Digital Finance on Maize Harvest Quality among Smallholder Farmers

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Abstract

Digital financial services offer much to smallholder farmers, though the benefits of these innovations are often unclear. There are value chain structures in maize that aim to improve market access, food security, and the overall profitability of the system. This study focuses on the effect of digital microfinance on maize harvest quality within the maize farming system in Central Java Province, Indonesia. This study surveyed 320 smallholder maize farmers in the four most productive regencies of the province. The constructs of Digital Microfinance Access (DMAI) and Harvest Quality Index (HQI) were operationalized across multi-dimensional finance and harvest quality. When evaluating the constructs, Access and Finance were treated as latent. The results of this study indicated that digital microfinance positively affected harvest quality and that the impacts were substantial. Access to digital microfinance significantly improves harvest quality outcomes, as indicated by an average marginal effect of 0.284. A one-unit increase in the Digital Microfinance Access Index (DMAI) is associated with a 0.284 increase in the Harvest Quality Index (HQI), holding other factors constant. However, in the case of digital farming classes, access to digital microfinance had an adverse effect, unlike in the three farming categories. Digital microfinance mobilizes liquidity and transforms maize farming from structural, qualitative, competitive, and transformational perspectives. The findings confirm that improved access to digital microfinance significantly enhances maize harvest quality, with measurable gains in key quality indicators and clear differences across farmer segments.

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Introduction

Developing policy frameworks for digital financial inclusion of smallholder farmers is crucial in countries without other options for digital credit (Kitole *et al.*, 2024; Ma and Rahut, 2024; Parlasca *et al.*, 2022). For the first time, 1.4 billion unbanked people can have access to mobile microfinance, fintech lending, and digital cooperative finance (Kitole *et al.*, 2024; Mendi and Matiwane, 2025). Agricultural microfinance is intended to alleviate liquidity constraints that hinder the effective management of farms and the use of farm inputs (Choudhury *et al.*, 2022; Ukwuaba *et al.*, 2025). Most of the global literature available focuses on the effects of digital finance on farmers' incomes and the technologies used on farms; the effects of digital finance on agricultural production and household food security are still underexplored. Rapid advancements in digital finance over the past couple of years have especially drawn the attention of many fintech companies to Integra's innovations in digital agriculture, for the first time in Indonesia (Nugraha *et al*., 2022; Soekarni *et al*., 2024). By 2025, over 65% of micro and small enterprises in Indonesia are projected to adopt digital finance (Setiawan *et al*., 2024). However, the availability of financial services remains uneven across sectors and regions. In maize farming, which is highly essential to the feed industry and food security, financing needs are time-critical and flexible. This is due to the seasonality and variability of production and yields, which are highly sensitive to input costs (Appiah-Twumasi *et al*., 2022; Zuhri *et al*., 2024). While maize production has risen in the country, smallholder farmers continue to face weaker market access and bargaining power due to the quality of the maize they produce, which tends to be moist, inconsistent, and poorly graded.

There is significant variation in the use of digital infrastructure and financial services in the Central Java Province. This is the heterogeneity that Widjaja *et al*. (2024) describe when referring to Central Java as an example of heterogeneity in digital and financial services and in maize production, where the province is a major player. It is pertinent to analyze how digital microfinance services are likely to address the quality gap among maize farmers. The existing work on financial farming and technology-driven inclusion contains some positive developments but also notable shortcomings. Access typically combines two or more metrics and/or volumetric loan measurements while ignoring other dimensions of the engagement (Ghosn *et al*., 2024; Kirchner and Musshoff, 2024). Furthermore, the majority of the studies reviewed also employed linear regression, which is inappropriate for best-case and quality measures that are constrained to pre-set (and often poor) ranges (Hembade *et al*., 2025; Sarfo *et al*., 2021). Some studies overlook the diversity of farmers' profiles, while others disregard distributional heterogeneity and zero in on average effect estimates (Ibrahim, 2022; Mahadik *et al*., 2025; Wahbi *et al*., 2023). Few studies have analyzed the heterogeneous impacts of digital microfinance on specific categories of farmers and the qualitative dimensions influencing those impacts.

One major gap in the literature is a trend where smallholder farmers are seen as a 'country' and treated as a homogenous group, when in reality they have many differences in the type of digital technologies that they adopt, from low-level basic mobile transactions to higher-level technologies, such as remote sensing and digital agronomy. To fill this gap, this study examines the impact of access to digital microfinance on maize harvest quality, explores the role of multidimensional components of access, and provides recommendations to tailor access and impacts of digital microfinance for heterogeneous farmer groups defined by varying access patterns and outcomes. The study utilizes an all-weighted framework composite index construction, engaging variety regression and latent class analysis to estimate both the total and heterogeneous effects of financial inclusion on the likelihood of using recommended practices to meet production quality. This research adds to the literature on how smallholders in developing economies experience digital agriculture.

Materials and Methods

A quantitative, cross-sectional research design was used in this study. Central Java Province in Indonesia, a heterogeneous region by access to digital finance and maize production systems, was chosen. Four regencies were chosen based on their importance in maize production and variation in agroecological and farming conditions and their availability of microfinance services: Grobogan, Blora, Wonogiri, and Kebumen.

Target Population Smallholder maize farmers in the 2025 cropping season Multistage cluster sampling was employed with the following approach: purposively select regencies, number of districts and villages randomly selected, and farmers randomly selected within each village. The total number of farmers surveyed was 320, which is approximately 6.4% of the estimated 5,025 populations. This sample size is sufficient for analytic techniques that involve the simultaneous estimation of multiple predictors and dependent variables (multivariate and latent-variable analyses), with sufficient statistical power and representation of farmer heterogeneity.

Data collection occurred from October to December 2025. The study examined farmers who used microfinance and digital financial services, as well as maize producers whose yields improved during the study.

Data Collection and Variable Measurement

There were many ways to gather information, such as conducting structured interviews with smallholder maize farmers. Preliminary research employed diverse methodologies and formats, including dual one-on-one interviews with maize farmers. The goal of these interviews was to learn everything there is to know about farmers, especially regarding digital microfinance services, financing terms, financial flexibility, digital financial literacy, and the quality of their harvests, including moisture content, kernel condition, uniformity, and compliance with minimum quality standards. We used a 5-point Likert scale to score opinion questions: often, sometimes, ever, rarely, and never. The questions were asked using either a ratio scale or a binary scale (0, 1), depending on whether the variable was present. We used primary data gathered in the same context to assess each variable. This improved content validity and increased the stability of the variables. We also used expert opinion and testing. To improve internal consistency and external observer comparability, composite indices were generated by standardizing all variables; these will form the basis for the econometric analysis. Table 1 display the definitions and measurements of the variables utilized in this study.

Table 1. Defining and measuring variables

Category	Variable	Indicator	Unit
Dependent variable	Harvest Quality Index (HQI)	Moisture content	%
		Physical kernel condition	Likert scale (1-5)
		Uniformity	Index (0-1)
		Quality standard compliance	Dummy (0/1)
Independent variable	Digital Microfinance Access Index (DMAI)	Platform accessibility	Likert scale (1-5)
		Disbursement speed	Days
		Financing flexibility	Likert scale (1-5)
		Integration with farm inputs	Dummy (0/1)
		Digital literacy	Likert scale (1-5)
Intermediate	Farm input utilization index	Input intensity	kg/ha
		Timeliness of input use	kg/ha
Control variables	Farm size	Land area	Hectare (ha)
	Farming experience	Years of farming	Years
	Education level	Formal education	Years
	Labor availability	Household labor	Persons
	Access to extension services	Extension contact	Dummy (0/1)
	Market access	Market linkage	Dummy (0/1)
Latent class ındicators	DMAI score	Digital finance engagement	Index (0-1)
	HQI score	Harvest quality performance	Index (0-1)

Exploratory Factor Analysis

Brown *et al*. (2022) focused on which factors determined by exploratory factor analysis (EFA) were meaningful in creating the Digital Microfinance Access Index (DMAI), an indicator of access to digital microfinance, and the Harvest Quality Index (HQI), a measure of harvest quality. The sampling adequacy was confirmed with the KMO measure, and Bartlett's Test of Sphericity was used to normalize variables. We kept factors with eigenvalues greater than or equal to 1 and disallowed any negative loadings lower than a threshold of 0.50 for the construct to be deemed valid at all. The original data for each variable were scaled within intervals of [0, 1] using min-max scaling and the composite indices obtained from summing the weighted scores for each variable. These indices were then rescaled to represent scores between 0 and 1, with 1 signifying the highest level of access and quality. Indices had their internal consistency assessed using Cronbach's alpha and were found to be internally consistent.

To clarify and standardize the method for generating the composite indices, we elucidated the steps involved in weighting and aggregating data. Because we had Types I and II factors with standard deviations of the EFA factor loadings, we began by normalizing each indicator using min-max scaling (Brown *et al*., 2022):

$$Xij = \frac{Xij - \min(Xj)}{\max(Xj) - \min(Xj)}$$

Where: *Xi* is the original value of indicator j for farmer i, and Xij′ is the normalized value that is between 0 and 1. Then, the normalized indicators were combined to form a composite index for each farmer.

$$CIi = \sum_{j=1}^{k} \mathrm{wj}.\mathrm{Xij}$$

Where: *CIi* is the composite index for farmer i (either DMAI or HQI), wj is the weight given to indicator j, and k is the total number of indicators.

Fractional Regression Model

Fractional regression model: As the dependent variable (the Harvest Quality Index or HQI) is a continuous index ranging between 0 and 1, a fractional regression model is the most appropriate to account for the semi-continuous variable. Fractional regression is more appropriate for proportional data than the structural equation modeling (SEM) or composite equation approaches used primarily for relationships between latent variables, which usually assume normally distributed outcomes. It also guarantees that predicted values are within the unit interval.

Even though we used exploratory factor analysis (EFA) to produce the composite indices, the focus of this study is on marginal effects instead of fitting elaborate latent structures. So, Thapa-Magar *et al*. (2024) follow a different approach, using a fractional regression model to generate improved, more credible, and more easily interpretable estimates of bounded outcomes in a manner aligned closely with the empirical objectives of the study. FRM can predict a dependent variable and constrain its predicted values in the classification ball, which means that FRM is a better way to estimate such variables than ordinary Least Squares (OLS) estimation. according to Thapa-Magar *et al*. (2024):

$$E\ (HQIi \mid Xi) = G\ (Xi\beta)$$

Where *HQIi* is the Harvest Quality Index of farmer i, constrained as a continuous variable in the unit interval [0, 1] (the 0-1 is expressed in a normalized fashion to maintain consistency through the units of the independent variables); Xi is a vector of independent variables (specifying which explanatory variables to include in the model, the Digital Microfinance Access Index (DMAI) index (which is also measured on a normalized index between 0 and 1 units) as well as control variables, measured in their natural units, hectares for farm size and years for farming experience and binary variables for access and measurement units); the estimates of β are the vector of parameters; and G (·) is a logistic link function, ensuring predicted values are bounded in the unit interval.

Where G (·) is a cumulative distribution function, typically the logistic function:

$$G(z) = \frac{1}{1 + e^{-z}}$$

The mean marginal effects (MME) were computed based on the fractional regression model, where the conditional expectation of the dependent variable is specified as a nonlinear function of the explanatory variable.

Latent Class Analysis Model and Class Interpretation Strategy

Barnes *et al*. (2020) conduct a latent class analysis (LCA) to identify class heterogeneity. In LCA you define the farmers as the population and the farmer class membership as the unobserved heterogeneity. The probability of a farmer is set to a characteristic vector Zi, where there can be a mixture of C class-specific probabilities as follows:

$$P(Zi) = \sum_{c=1}^{C} \pi_c . P(Zi \,\mathrm{I}\, C_i = c)$$

with C as the number of latent classes and πc as the class membership probability, which indicates that a farmer belongs to class c (where class membership probabilities sum to 1 and range from 0 to 1). P (Zi|Ci=c) is the likelihood that an individual observation (Zi) is observed, given that the individual belongs to class c, and Ci is the unobserved class membership of farmer i.

The vector Zi includes both observed variables, such as the Digital Microfinance Access Index (DMAI), which is measured on a scale from 0 to 1, and control variables, such as farm size (in hectares), years of farming experience, and binary indicators of access. We also model class membership as a function of these variables, with each class having its own intercept (αc) and coefficients (γc) that show how the explanatory variables affect the chance of belonging to that class.

Statistical Analysis

The data analysis was conducted using IBM SPSS Statistics version 28. Exploratory factor analysis was used to create the composite indices. The two composite indices that were created are the Digital Microfinance Access Index (DMAI) and the Harvest Quality Index (HQI). Factor extraction is performed using the principal component approach, and simplification is achieved through varimax rotation. The reliability test for the construct is measured using Cronbach's alpha.

Results and Discussion

Exploratory factor analysis in the development of composite indices and the validation of constructs

Based on the results in Table 2, both the DMAI and HQI meet the criteria for conducting factor analysis, as the KMO values are above 0.80. Moreover, Bartlett's Test of Sphericity indicates that the variables are related, as the p-value is less than 0.001. Furthermore, it should be noted that all factors loaded at more than 0.50, with standardized factor loadings ranging from 0.62 to 0.84, indicating that the constructs contribute significantly to the indicators. The total explained variance of 63.4% reported in Table 2 further indicates that the extracted factors capture a substantial proportion of the data variability, implying that the constructed indices (DMAI and HQI) provide a reliable and valid representation of the multidimensional characteristics of digital financial access and maize harvest quality among smallholder farmers.

Basic metrics related to financial literacy are less valuable to providers of digital financial and credit services than transaction or customer engagement metrics (even rudimentary ones). This shows that the digital component carries significant weight in the DMAI. This further supports Wang *et al*. (2024), which shows that financially active digital users are more commercially important for financial inclusion than financially inactive digital users. In the harvested quality index (HQI) dimension, the most important parts are harvesting quality and harvest uniformity. This shows that the value of harvested maize is based on its quality. This is consistent with Kashyap and Bhuyan (2023) in India, who state that for market access and price discrimination, the quality of a product in its tangible form is, contrary to other factors, the most important. Personalized marketing may distort short-term market signals, particularly in oligopolistic or monopolistic market structures.

Table 2. Exploratory factor analysis results for composite indices

Indicator	Factor loading	Standardized loading	Communality
Digital Microfinance Access Index (DMAI)			
Platform accessibility	0.78	0.75	0.61
Disbursement speed	0.74	0.71	0.55
Financing flexibility	0.71	0.69	0.50
Integration with farm inputs	0.69	0.66	0.48
Digital literacy	0.81	0.79	0.66
Harvest Quality Index (HQI)			
Moisture content control	0.76	0.73	0.58
Physical kernel condition	0.73	0.70	0.53
Kernel uniformity	0.70	0.68	0.49
Compliance with quality standards	0.68	0.65	0.46
Model adequacy statistics			
Kaiser-Meyer-Olkin (KMO): 0.81			
Bartlett's Test of Sphericity: χ^2 = 1,247.6; $p < 0.001$			
Total variance explained: 63.4%			

Notes: Only indicator loadings above 0.50 were retained. Exploratory Factor Analysis was performed using IBM SPSS Statistics, employing principal component extraction and varimax rotation.

In contrast to simple arithmetical aggregation, index construction using Exploratory Factor Analysis (EFA) enables one to empirically validate departures from the assumption of equal weighting, thereby offering greater methodological precision and yielding a more substantial index value than other methods. In less-than-equal weighting, EFA index construction rests on the strongest empirical basis for providing enhanced index values. From an empirical perspective, this offers a highly effective methodology for statistically testing the multidimensional nature of the simultaneity between digital financial inclusion and the quality of the farmers' harvests.

Table 3 depicts the contribution of each variable in determining the index value, as reflected by standardised factor loadings based on exploratory factor analysis. Also included in this table are the means (scaled between 0 and 1) and associated standard deviations for the various factors that highlight important dimensions of digital financial access and maize harvest quality.

For DMAI, on the other hand, standardised mean values range from 0.55 to 0.67, which indicates that farmers have access to digital microfinance relatively well. Two specific categories of digital literacy (0.67) and access to the platform (0.65) are distinguished by the maximum mean values, respectively. This implies that the mean values of digital capability and digital accessibility of the platform offer a capacity for enhancing financial inclusion. In comparison, a relatively weaker integration of 0.55 signifies the disassociation between financial inclusion and agriculture. This observation is in line with EFA results, which indicate that the weight coefficients are higher for important variables.

The DMAI and HQI may thus provide similar information, though HQI is more stable for farmers than access to digital microfinance, and both rates are moderate. This could be due to reliance on traditional agriculture and experience with harvest management, despite still early stages of financial digitalisation within the community. This result is in agreement with those obtained by Kazimierczak *et al*. (2024), which show that better production can occur without, or prior to, the financial system being digital.

Table 3. Weights and scores for the composite index

Indicator	Factor Weight (dimensionless)	Mean score	Standard deviation
Digital Microfinance Access Index (DMAI)			
Platform accessibility	0.15	0.65	0.21
Disbursement speed	0.14	0.62	0.19
Financing flexibility	0.13	0.64	0.20
Integration with farm inputs	0.12	0.55	0.19
Digital literacy	0.16	0.67	0.22
Harvest Quality Index (HQI)			
Moisture content control	0.11	0.61	0.18
Physical kernel condition	0.10	0.63	0.17
Kernel uniformity	0.09	0.54	0.13
Compliance with quality standards	0.10	0.57	0.18
Total	**1.00**		

Source: Processed data using IBM SPSS Statistics.

By merging both indices into one analytical framework, an exhaustive assessment of the linkage between production outcomes and financial inclusion in the population can be performed. The approach helps to develop holistic knowledge for smallholder agricultural development by combining both an analysis of the enabling conditions (access to finance) and the analyses of the outcomes (harvest quality) using DMAI and HQI, respectively. In this context, Hailu *et al*. (2025) highlight that we need multidimensional approaches to measure agricultural and economic impacts, yet studies in emerging rural economies tend to treat financial inclusion and production performance separately.

The structural relationships among digital microfinance access, intermediary variables, and harvest quality performance are illustrated in Figure 1, providing a conceptual overview of how the Digital Microfinance Access Index (DMAI) influences input use behaviour and, in turn, affects the Harvest Quality Index (HQI). This figure highlights the hypothesized pathways and interaction mechanisms underlying the empirical model tested in this study.

Most of the empirical data shown in Figure 1 is relatively moderate to large in terms of HQI and moderate in terms of DMAI. These show an average level of harvest quality rather than engagement in digital microfinance. It also shows that some farmers can achieve high harvest quality even when conditions are unfavourable.

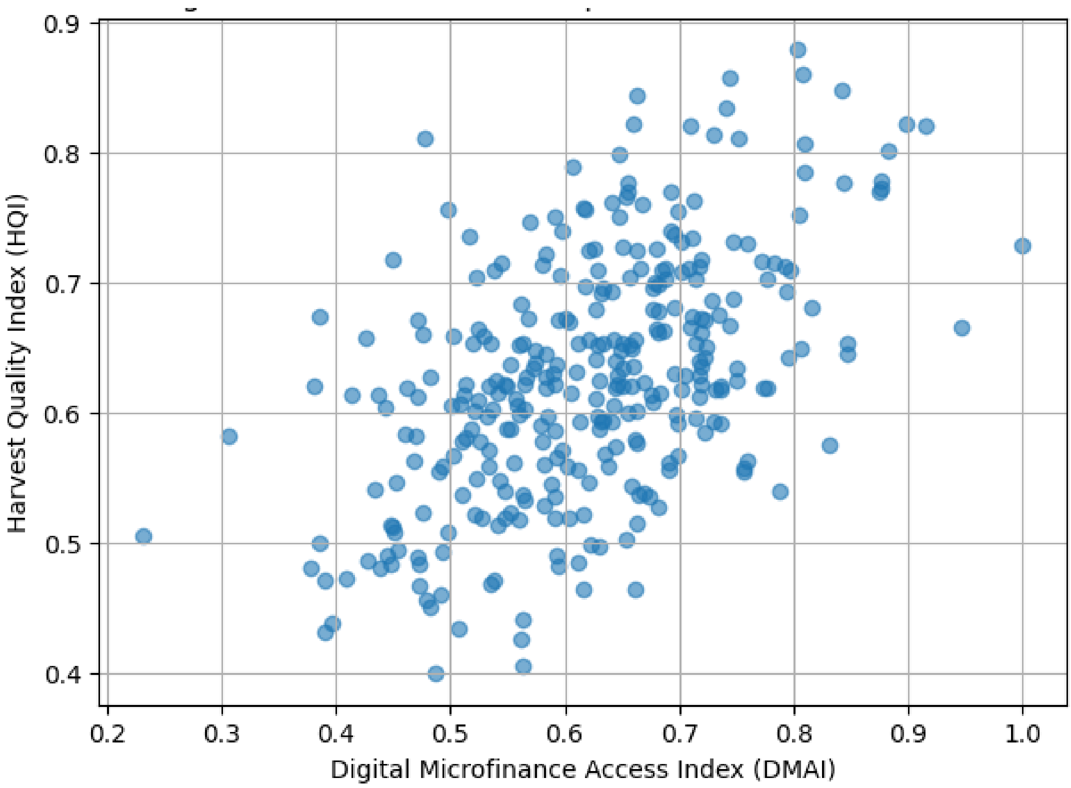

Figure 1. Distribution of the composite index: DMAI compared to HQI

What holds here is a mean-asymmetrical-skewed distribution, which is true for most farmers with low DMAI and high HQI. This shows that some farmers can achieve a high level of production quality even when their engagement with the digital financing system is low. This may be due to the presence of formal financing or robust informal financing within the local informal financing system. Babenko *et al*. (2025) report a similar digital finance scenario in Kazakhstan, where improving digital financial services risk management for the low economic and financially poor in the country is of great value, given the country's governance and market conditions.

The combined analytical framework, utilizing two validated composite indices, provides initial-stage analysis and visualization of indices, along with the initial detection of heterogeneity. This framework advances beyond simplistic mean-based approaches by enabling the modelling of structural and behavioural heterogeneity among maize farmers, using techniques such as Fractional Regression and Latent Class Analysis.

Estimation of Harvest Quality Determinants Using Fractional Logit Models

A positive, significant relationship is identified between the Digital Microfinance Engagement (DME) and the Harvest Quality Index (HQI) variables (Table 4). This means that farmers' harvest quality improves as they access DME services. Among all the fractional regression models, this one stands out best as it Most closely aligns with the findings by Mao *et al*. (2022) as they describe this model as the best for estimating the case of the dependent variable of interest being constrained to the (0, 1) interval as it avoids out of bound predictions and aids in consistency of estimating the model parameters. The positive value for this parameter suggests that the financial services accessed improved farmers' finances, the quality of agri inputs, and overall farming and post-harvest management.

As reported in Table 4, the model yields a pseudo-R^2 of 0.312. While this value may appear modest when compared to the coefficient of determination in linear regression models, it is considered acceptable and reasonably strong in the context of fractional regression models. Unlike conventional R^2, Pseudo R^2 does not represent the proportion of variance explained, but rather indicates the improvement of the fitted model relative to a null model. Consequently, a value of

0.312 indicates considerable improvement in explaining the phenomenon and the association between digital microfinance access and harvest quality performance.

Table 4. Fractional regression model estimation

Variable	Coefficient	Std. error	Z-stat	Sig.
Digital Microfinance Access Index (DMAI)	0.842	0.112	7.52	***
Farm size (ha)	0.156	0.068	2.29	**
Farmer experience (years)	0.021	0.009	2.33	**
Education level (years)	0.034	0.014	2.43	**
Access to extension services (dummy)	0.118	0.053	2.23	**
Cooperative membership (dummy)	0.097	0.049	1.98	*
Constant	-0.624	0.181	-3.45	***
Fractional logit model				
Dependent variable: Harvest Quality Index (HQI)				
Pseudo R^2 = 0.312				
Number of observations = 320				

Notes: ***, ***, and * show significance at the 1%, 5%, and 10% levels.

Various earlier studies have shown that digital finance is significant for agriculture. For instance, Francis *et al*. (2022) show that digitalizing financial services increases the productivity of smallholder farmers in Ghana. Likewise, Abdullah *et al*. (2024) highlight the evolving relationship between financing techniques and agricultural productivity, where enhanced digital finance services contribute to productivity improvements by reducing digital illiteracy.

Nevertheless, most of the literature highlights the barriers to digital literacy and emphasizes the adverse implications of digital illiteracy for financial inclusion. Conversely, these restrictions are not prominent in the current study, where farmers use digital financial services moderately. The proposed research adds value to the existing literature by combining the composite index method with a fractional regression model to determine the association between digital microfinance access and harvest quality.

Table 4 shows the strength and statistical significance of the connection, while Table 5 uses Average Marginal Effects (AME) to explain it. The AME figures measure the mean change in the Harvest Quality Index (HQI) per unit increase in the independent variable. Among the independent variables, engagement in digital microfinance is positively associated with the proportion of the HQI. The policy significance of the marginal effects is further enhanced by documenting them, as they characterize the logit coefficients in practical utility and relevance by describing changes in likelihoods.

Table 5. Average marginal effects from the fractional regression model

Variable	Marginal effect	Std. error	Sig.
Digital Microfinance Access Index (DMAI)	0.284	0.041	***
Farm size (ha)	0.052	0.023	**
Farmer experience (years)	0.007	0.003	**
Education level (years)	0.011	0.005	**
Access to extension services (dummy)	0.038	0.017	**
Cooperative membership (dummy)	0.031	0.016	*

Notes: ***, **, and * signify significance at the 1%, 5%, and 10% levels, respectively.

Hu *et al*. (2023) argue that due to non-linear sensitivity and possibly larger impacts, marginal effects may be more applicable. Khan *et al*. (2023) show that unadjusted empirical logit coefficients under-estimate the impact of productivity arising from agricultural finance. Moreover, the robust AME estimates from the digital finance study, coupled with the fact that the digitisation of agricultural finance is linked to more abundant harvests, warrant strong impact assumptions. Simple correlation methods would fail in this case. This study is pivotal in that, unlike any other, it demonstrates the use of marginal effects with the harvest quality index, which has been authenticated via EFA. This is paramount because it confirms that the estimated marginal effects are multidimensional, not unidimensional, and not focused solely on yield and/or output price.

An illustration of the expected mean marginal effects of explanatory variables on HQI is shown in Figure 2. It provides a visual display not only of the direction and strength but also of the confidence intervals for each explanatory variable's effect on the HQI, making it easier to analyse the influence of DMAI and other control variables on maize harvest quality for small-scale farmers.

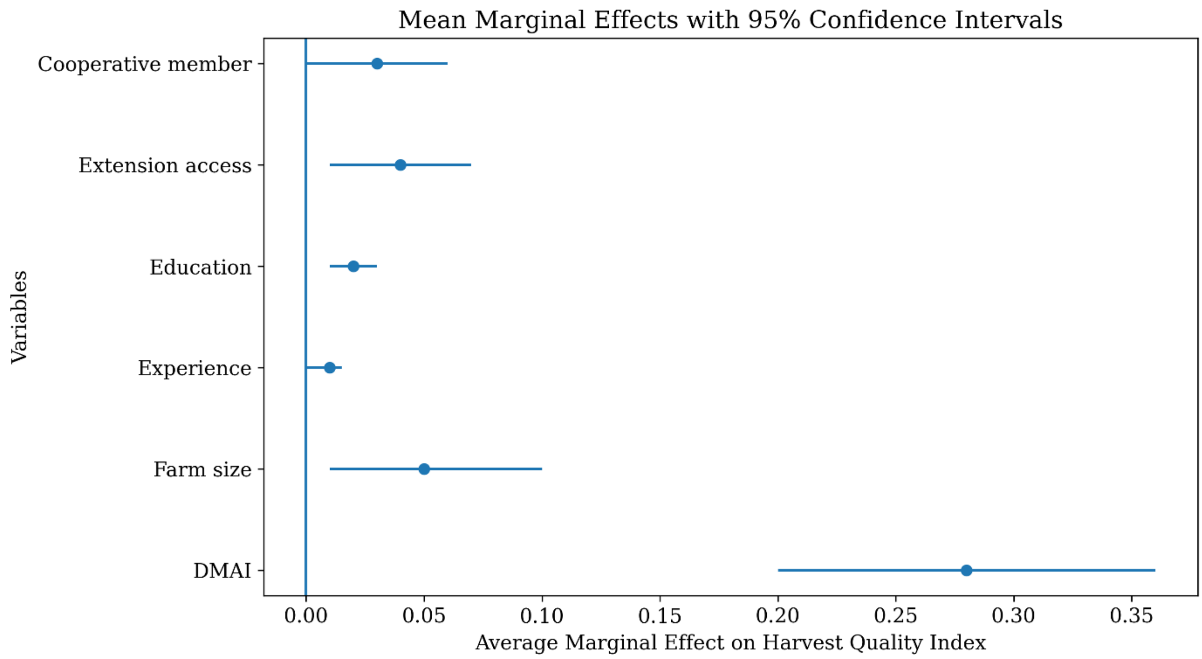

Figure 2. Average marginal effects of access to digital microfinance on harvest quality

From the provided data, we can see the range of balance of the Harvest Quality Index (HQI) and the usage of digital microfinance (Figure 2), an example of which can go from a decline of usage in low and collateral capture microfinance usage throughout the HQI value range, and an example of a micro finance digital usage capture in the collateral low range as an example of a digital microfinance digital usage capture in the collateral low range of the value range and as a function of digitized digital use capture as an example of a hyperbolic function. Value as a digital non-linear capture function is an example of a hyperbolic function.

The clearest example of the above is Sisay (2024), who observed that accessible banking increased the financial inclusion of Ethiopian households, with the most significant effect on households that had previously been unbanked. Gao *et al.* (2024) also observed this among previously unbanked farmers, contrasting their productivity with that of established farmers, whose productivity was lower. The most significant contributions of this research are the recording of fractional regression and marginal effects, which illustrate how digital microfinance interventions are most efficiently targeted to farmers with little to moderate digital financial inclusion and how greater digital financial integration among farmers responds positively to greater microfinance interventions.

Farmer Heterogeneity and Segmentation: Results from Latent Class Analysis

When examining Table 6, the three-class model is more appropriate than the two-class and four-class models based on multiple model fit criteria. Specifically, the three-class model reports the lowest values of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and adjusted Bayesian Information Criterion (adjusted BIC), indicating a better model fit with optimal parsimony. In addition, entropy value greater than 0.80 suggests a high level of classification accuracy, meaning that individuals are well distinguished across latent classes. The Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) is statistically significant for the two- and three-class models but not for the four-class model, further supporting the selection of the three-class solution. Overall, the three-class model provides the best balance between model fit, classification quality, and explanatory power among the competing alternatives.

Table 6. Fit of the latent class model and selection criteria for the classes

Number of classes	Log-likelihood	AIC	BIC	Adjusted BIC	Entropy	LR test (p-value)
1-Class Model	-412.38	846.76	879.21	851.34	-	-
2-Class Model	-368.52	769.04	823.67	776.81	0.79	0.000
3-Class Model	-341.27	726.54	803.35	737.48	0.83	0.000
4-Class Model	-336.91	729.82	828.81	743.93	0.71	0.118

Note: The optimal class number is selected based on the lowest AIC/BIC values, the statistically significant results from the LR tests, and the highest entropy values. Total observations = 320.

As shown in Table 6, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) yields a p-value of 0.118 for the comparison between the three-class and four-class models. This value is not statistically significant at conventional levels ($p > 0.05$), indicating that the four-class model does not provide a significantly better fit than the three-class model. Therefore, adding class does not meaningfully improve the model, supporting the selection of the more parsimonious three-class solution.

As Delphino *et al*. (2023) demonstrate, both BIC and entropy are reliable and stable methods for selecting the number of latent classes. In this regard, according to Schambow *et al.* (2023), three classes would be the best choice for studying productivity heterogeneity among smallholders in Latin America's agricultural industry, as this option allows maintaining the optimal balance.

This study differs from others in using LCA for DMAI and HQI for the first time. These are composite indices, not single observed variables like in most studies. This means that the segmentation LCA looks at more than just social and demographic factors. It also examines a multidimensional variable measuring digital financial integration and the quality of production. This is much deeper and gives a better explanation of why maize farmers are so different.

Table 7 summarises the profiling characteristics of the latent classes identified. It also illustrates how major metrics and variables are dispersed across each segment. This table compares these differences between farmers to structural, behavioural, and production-related traits that differentiate each class of farmer in the maize farming system.

The categorization of maize farmers and the Digital Microfinance Access Index (DMAI) and HI scores of farmers are shown in Table 7. Farmers represent 34% of the sample and have the lowest DMAI and HI scores. Also, HI farmers account for 41% of the sample and have DMAI and HI in the moderate range. These farmers are described as transitional because they have partially adopted digital spades. Among the DMAI, those with HI below 25% are the Digital Microfinance Access Index (DMAI). Comparisons of the three segments' indices show significant differences. This validates the segmentation and affirms that the segmentation is not a statistical artifact.

The segmentation of maize farmers is similar to the classification of the farmers into early adopters, early majority, and non-adopters. This classification aligns with digital financial services adoption, as shown in Shi *et al*. (2022). Chi households were the first to employ digital financial services for micro-level household management and investment. The study also showed that the use of digital services extended beyond financing to the production of high-quality crops.

Table 7. Maize farmers' latent class profiles deriving from DMAI and HQI

Variable	Class 1: Digitally Constrained (n = 98; 30.6%)	Class 2: Transitional Adopters (n = 137; 42.8%)	Class 3: Digitally Empowered (n = 85; 26.6%)
Digital Microfinance Access Index (DMAI)	0.41	0.63	0.82
Digital payment usage	0.38	0.67	0.88
Access to an online credit platform	0.29	0.58	0.84
Loan approval speed	0.46	0.64	0.79
Financial literacy score	0.44	0.62	0.81
Harvest Quality Index (HQI)	0.52	0.64	0.77
Moisture compliance rate	0.55	0.69	0.82
Physical grain quality score	0.51	0.63	0.75
Post-harvest loss control	0.49	0.60	0.74
Average farm size (ha)	0.58	0.83	1.12
Extension access (%)	34%	61%	79%
Cooperative membership (%)	29%	54%	72%

Note: The total sample size for this specific class is 320 farmers. The class proportions are calculated as posterior probabilities of membership.

As previously observed, innovation within non-digital value chain classes, particularly in relation to positive production traits, may leverage agroforestry practices, local socio-cultural systems, or other context-specific approaches within a conventional production system to enhance harvest outcomes without reliance on digital financing. This once again shows the effects of digitalization in the agricultural sector, as well as the evidence of policy differentiation in contrast to the one-size-fits-all policy.

The distribution and relative attributes of the discovered farmer segments are shown in Figure 3, making it easy to see how the farmers differ according to the latent-class segmentation results. The illustration reveals some relative differences among farmers in digital finance, production practices, and harvesting practices.

The self-reinforcement in the index of class divergence, as exhibited in Figure 3, has been previously noted and is consistent with the class interpretation of the above table. Class Three's profile line is consistently the highest in all the DMAIs and HQIs. In contrast, Class One is the most extreme across all cases, particularly in the dimensions of the absence of available digital credit and the extent of app transactional multiplicities. Class Two, as a stable class, is positioned such that a desirable continuum is achieved with respect to the other classes. The profile lines, which represent the classes, diverge to illustrate the uneven spread of the integrated finance with the production economy.

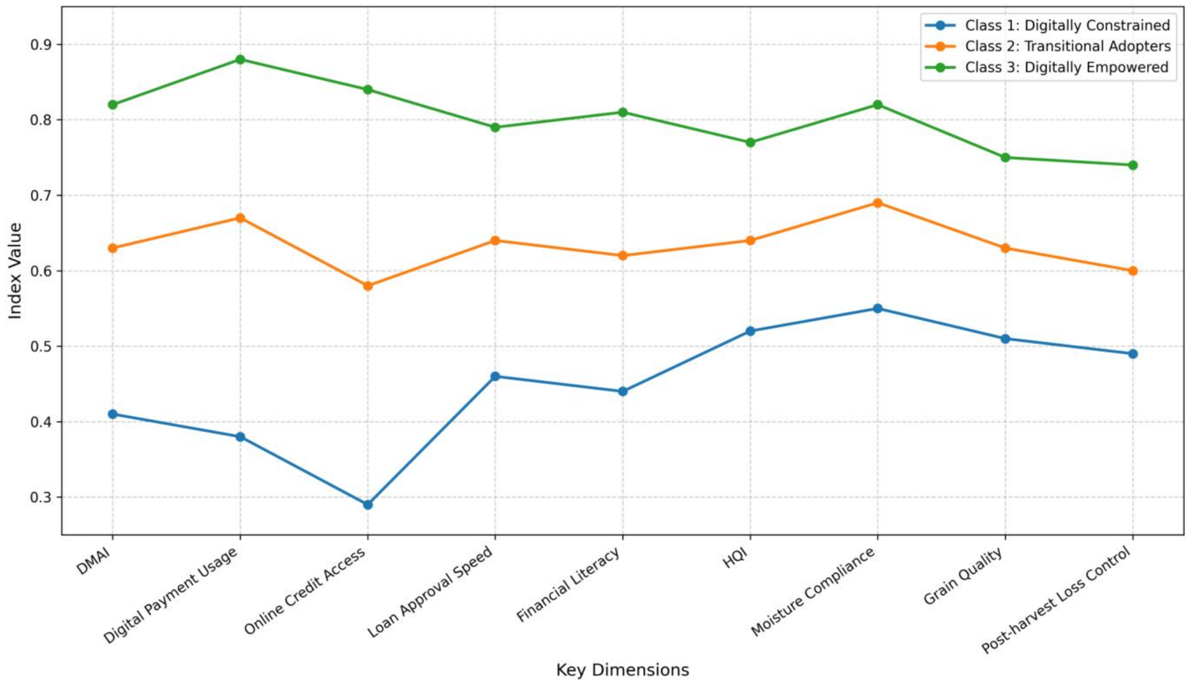

Figure 3. Profiles of latent classes with respect to access to digital microfinance and quality of harvests

The simplest form of dual engagement shows a clear co-movement. Class three shows movement among the indices. For class three, we note the enhanced quality of production and digital financial services. The other classes parallel Camacho-Villa *et al*. (2023) on agri-financing and productive investments in Mexico. In the second class, the non-linear observations of the indices reveal that only small increases in HQI were observed alongside increases in small and DMAI. This is indicative of a threshold effect or of other factors, be they managerial or related to market access.

The most pertinent findings are the use of a Composite Index, the Fractional Regression Model, and Latent Class Analysis. The purpose of the research is to identify latent classes associated with the composite indices, of which two factors have been validated. Hence, the research offers a holistic perspective on digital transformation and the quality of production by smallholder maize farmers. The relatively finer constituents or indicators presented here must be applied to segment the indices or target policy groups. This is comparatively superior and shows significant progress relative to older, much coarser controlled or aggregated methods for differentiated/targeted policy approaches.

What is the impact of digitally enabled microfinance integration with agricultural harvesting on the specificity of results? As the use of digital financial services becomes more widespread, farmers' outputs rise in all physical quality dimensions. Quality of the harvests Digital Financial Services (DFS) combined all farmers' outputs and increased the physical quality of the harvests. There is a range of diagnostic digital financing policy impacts, coupled with a modern digital infrastructure and a management and operational framework for economically configuring productive resources into the desired productive actions. To avoid indiscriminate digital integration in agriculture, integrating policy evidence is critical.

This work analyses, using the Theory of Strategic Outcomes, the impact of Digital Financial Inclusion (DFI) on the agricultural development of rural farmers in the Global South. DFI focuses on the quality of the harvest rather than the more prevalent, reductionist measures of productivity and/or monetized outcomes. Considering the rural farming populace of the Global South, their heterogeneity and structural relations, the fusion of several Multidimensional indices, bounded fractional regression, and Latent Class Segmentation (LCS) would more accurately capture this scenario. Digital Microfinance (DMF) is expected to be positioned within a more traditional approach to agrarian development, going beyond instrumental financing to focus on quality, competitiveness, and sustainability.

Conclusions

The results show that digital microfinance access has a positive, statistically significant effect on harvest quality, with mean marginal effects indicating it is the most influential factor among the control variables. It shows that better access to digital financial services can improve farmers' capability in input management, better practices, and quality compliance. In addition, the latent class analysis identifies considerable differences among the farmer respondents, indicating three farmer segments based on their level of digital financial service access, production activities, and harvesting performance. The three-class latent model is validated using several model fit statistics, including AIC, BIC, entropy, and the Lo-Mendell-Rubin test, indicating that digital microfinance improves agricultural upgrading but works best with specific segments. Thus, policymakers can intervene in digital finance initiatives for agricultural upgrading by adopting an effective approach, such as designing programs that target farmer segments based on their characteristics and access conditions. The present study adds to the literature by combining econometric and segmentation analyses to understand better the contribution of digital finance initiatives to agricultural development. Nevertheless, the findings of this study are limited to maize farmers in Central Java, and further research is needed using a longitudinal, experimental study design.

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Conflict of interest

The authors declare no conflict of interest.

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Author Contribution

The conceptualization of the research, the formulation of methodology, the formal analysis, and the drafting of the first draft were performed by N. M. Z. The investigation, data curation, and validation were done by N. A. The supervision, the improvement of the methodology, and the critical review of the manuscript were performed by Z. R. and N. M. S. A. All authors read, approved the final manuscript, and its submission to the journal.

References

Abdullah, R., Najim, M. M. M., and Esham, M. (2024). Agriculture for Sustainable Development to Empower Smallholder Farming Communities. *Journal of Agricultural Sciences - Sri Lanka*, *19*(3), 462–474. https://doi.org/10.4038/jas.v19i3.10831

Appiah-Twumasi, M., Donkoh, S. A., and Ansah, I. G. K. (2022). Innovations in Smallholder Agricultural Financing and Economic Efficiency of Maize Production in Ghana’s Northern Region. *Heliyon*, *8*(12), 1-15. https://doi.org/https://doi.org/10.1016/j.heliyon.2022.e12087

Babenko, T., Kolesnikova, K., Panchenko, M., Abramkina, O., Kiktev, N., Meish, Y., and Mazurchuk, P. (2025). Risk Assessment of Cryptojacking Attacks on Endpoint Systems: Threats to Sustainable Digital Agriculture. In *Sustainability, 17*(12), 1-36. https://doi.org/10.3390/su17125426

Barnes, A. P., Thompson, B., and Toma, L. (2022). Finding The Ecological Farmer: A Farmer Typology To Understand Ecological Practice Adoption Within Europe. *Current Research in Environmental Sustainability*, *4*, 1-10. https://doi.org/https://doi.org/10.1016/j.crsust.2022.100125

Brown, K., Schirmer, J., and Upton, P. (2022). Can Regenerative Agriculture Support Successful Adaptation To Climate Change and İmproved Landscape Health Through Building Farmer Self-Efficacy and Wellbeing? *Current Research in Environmental Sustainability*, *4*, 1-13. https://doi.org/https://doi.org/10.1016/j.crsust.2022.100170

Camacho-Villa, T. C., Zepeda-Villarreal, E. A., Díaz-José, J., Rendon-Medel, R., and Govaerts, B. (2023). The Contribution Of Strong and Weak Ties to Resilience: The Case of Small-Scale Maize Farming Systems İn Mexico. *Agricultural Systems*, *210*, 1-10. https://doi.org/https://doi.org/10.1016/j.agsy.2023.103716

Hembade, S. C., Yelikar, B. V., Mahadik, R. V., Ayarekar, S., Desai, S., and Yadav, J. S. (2025). Mapping Administrative Models for Cost Effective Microinsurance Delivery to Rural Farmers. *Enterprise Development and Microfinance*, *35*(1), 177-187. https://papjournals.com/index.php/edm/article/view/14

Choudhury, A., Jones, J., and Opare-Addo, M. (2022). Perceived Risk and Willingness to Provide Loan to Smallholder Farmers in Ghana. *Journal of African Business*, *23*(1), 23–40. https://doi.org/10.1080/15228916.2020.1773732

Delphino, M. K. V. C., O'Brien, N., Laurin, E., Whelan, D., Burnley, H., Hammell, K. L., and Thakur, K. K. (2023). Bayesian Analysis of Diagnostic Sensitivity and Specificity For Detecting İnfectious Salmon Anaemia Virus (ISAV) Using IFAT And Real-Time RT-PCR Testing From Laboratories İn Atlantic Canada. *Aquaculture*, *563*, 739006. https://doi.org/https://doi.org/10.1016/j.aquaculture.2022.739006

Francis, K., Dongying, S., Dennis, A., Edmund, N. N. K., and Kumah, N. Y. G. (2022). Network Governance And Renewable Energy Transition in Sub-Saharan Africa: Contextual Evidence From Ghana. *Energy for Sustainable Development*, *69*, 202–210. https://doi.org/https://doi.org/10.1016/j.esd.2022.06.009

Gao, Q., Cheng, C., Sun, G., and Li, J. (2022). The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: Evidence From China. *Frontiers in Ecology and Evolution*, *10-1-11*. https://doi.org/10.3389/fevo.2022.905644

Ghosn, F., Zreik, M., Awad, G., Tahan, S., and Ashaal, A. (2024). Enhancing Financial İnclusion in China Amidst COVID-19: Opportunities, Challenges, And Strategies. *Journal of Infrastructure, Policy and Development*, *8*(6), 1–19. https://doi.org/10.24294/jipd.v8i6.3777

Hailu, A. A., Thornhill, S., Tessema, M., Weldesilassie, A. B., and Lahiff, E. (2025). The İnfluence of The Food Environment On Diet Quality: Insights From An Extensive Household Survey in Ethiopia, Focusing On Women of Reproductive Age. *BMC Nutrition*, *11*(1), 1-19. https://doi.org/10.1186/s40795-025-01097-z

Hu, J., Zhang, H., and Irfan, M. (2023). How Does Digital İnfrastructure Construction Affect Low-Carbon Development? A Multidimensional İnterpretation of Evidence From China. *Journal of Cleaner Production*, *396*, 136467. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.136467

Ibrahim, B. E. D. A. (2022). Lessons for African Microfinance Providers and Regulators in The Aftermath of COVID-19. *Enterprise Development and Microfinance*, *33*(3), 182–191. https://doi.org/10.3362/1755-1986.21-00020

Kashyap, D., and Bhuyan, S. (2023). Accessing Value-Added Market Through Cooperatives: A Case Study of Sitajakhala Dugdha Utpadak Samabai Samiti Ltd., India. *Journal of Agribusiness* *in Developing and Emerging Economies*, *13*(3), 399–417. https://doi.org/10.1108/JADEE-05-2021-0131

Kazimierczak, R., Obidzińska, J., Szumigaj, B., Dobrowolski, H., and Rembiałkowska, E. (2024). Sustainable foods: Consumer opinions and behaviour towards organic fruits in Poland. *Sustainability*, *16*(9), 1-21. https://doi.org/10.3390/su16093740

Khan, N., Ma, J., Zhang, H., and Zhang, S. (2023). Rural Farmers' Perceptions for the Impacts of Climate Change and Adaptation Policies on Wheat Productivity: Insights from a Recent Study in Balochistan, Pakistan. In *Atmosphere, 14*(8), 1-18. https://doi.org/10.3390/atmos14081278

Kirchner, E., and Musshoff, O. (2024). Digital Opportunities for The Distribution of İndex-Based Microinsurance: Evidence From A Discrete Choice Experiment in Mali. *Journal of Agricultural Economics*, *75*(2), 794–815. https://doi.org/https://doi.org/10.1111/1477-9552.12584

Kitole, F. A., Mkuna, E., and Sesabo, J. K. (2024). Digitalization and Agricultural Transformation in Developing Countries: Empirical Evidence from Tanzania Agriculture Sector. *Smart Agricultural Technology*, *7*, 1-10. https://doi.org/https://doi.org/10.1016/j.atech.2023.100379

Ma, W., and Rahut, D. B. (2024). Climate-Smart Agriculture: Adoption, İmpacts, and İmplications for Sustainable Development. *Mitigation and Adaptation Strategies for Global Change*, *29*(5), 44. https://doi.org/10.1007/s11027-024-10139-z

Mao, P., Zhang, J., Li, M., Liu, Y., Wang, X., Yan, R., Shen, B., Zhang, X., Shen, J., Zhu, X., Xu, D., and Xin, X. (2022). Spatial and Temporal Variations in Fractional Vegetation Cover and its Driving Factors in the Hulun Lake Region. *Ecological Indicators*, *135*, 1-10. https://doi.org/https://doi.org/10.1016/j.ecolind.2021.108490

Mendi, G., and Matiwane, M. (2025). Determinants of the Barriers Preventing Smallholder Farmers from Adopting Conservation Agriculture in Hazyview, Mpumalanga, South Africa. *South African Journal of Agricultural Extension*, *53*(4), 20-38. https://doi.org/10.17159/2413-3221/2025/v53n4a16942

Nugraha, D. P., Setiawan, B., Nathan, R. J., and Fekete-Farkas, M. (2022). Fintech Adoption Drivers for Innovation for SMEs in Indonesia. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(4), 1-16. https://doi.org/https://doi.org/10.3390/joitmc8040208

Parlasca, M. C., Johnen, C., and Qaim, M. (2022). Use of Mobile Financial Services Among Farmers in Africa: Insights from Kenya. *Global Food Security*, *32*, 1-10. https://doi.org/https://doi.org/10.1016/j.gfs.2021.100590

Sarfo, Y., Musshoff, O., Weber, R., and Danne, M. (2021). Farmers' Willingness to Pay for Digital and Conventional Credit: Insight From a Discrete Choice Experiment in Madagascar. *PLOS ONE*, *16*(11), 1-23. https://doi.org/10.1371/journal.pone.0257909

Schambow, R., Giménez-Lirola, L. G., Hanh, V. D., Huong, L. T. L., Lan, N. T., Trang, P. H., Luc, D. D., Bo, H. X., Chuong, V. D., Rauh, R., Nelson, W., Mora-Díaz, J. C., Rovira, A., Culhane, M. R., and Perez, A. M. (2023). Modeling the accuracy of a novel PCR and antibody ELISA for African swine fever virus detection using Bayesian latent class analysis. *Frontiers in Veterinary Science*, *10*, 1-13. https://doi.org/10.3389/fvets.2023.1079918

Setiawan, B., Phan, T. D., Medina, J., Wieriks, M., Nathan, R. J., and Fekete-Farkas, M. (2024). Quest for Financial İnclusion Via Digital Financial Services (Fintech) During COVID-19 Pandemic: Case Study of Women in Indonesia. *Journal of Financial Services Marketing*, *29*(2), 459-473. https://doi.org/10.1057/s41264-023-00217-9

Shi, B., Wang, S., Jiao, J., Li, G., and Yin, C. (2022). Recognition on Characteristics and

Applicability of Typical Modes for Manure and Sewage Management in Pig Farming: A Case Study in Hebei, China. *Waste Management*, *148*, 83–97. https://doi.org/https://doi.org/10.1016/j.wasman.2022.05.018

Sisay, K. (2024). Wellbeing, Productivity and Food Security Effects of Multiple Livelihood Diversifications: Insight from Kaffa Zone, Ethiopia. *Cogent Social Sciences*, *10*(1), 1-23. https://doi.org/10.1080/23311886.2023.2282211

Soekarni, M., Adam, L., Thoha, M., Sarana, J., Ermawati, T., Saptia, Y., Adityawati, S., Sujianto, and Wibowo, M. (2024). Strengthening Financial Literacy of Smallholder Farmers Through Agricultural Fintech Peer-To-Peer Lending: Evidence and Practical İmplications. *Cogent Social Sciences*, *10*(1), 1-14. https://doi.org/10.1080/23311886.2024.2359011

Thapa-Magar, D. B., Pandit, R., and Fay Rola-Rubzen, M. (2024). Drivers of Overseas Labour Migration, Migration İntensity, and Destination Choice Among Farming Households in Nepal. *Journal of Ethnic and Migration Studies*, *50*(18), 4459–4483. https://doi.org/10.1080/1369183X.2024.2373311

Ukwuaba, I. C., Nze, C. B., Mukaila, R., Ukwuaba, S. I., Ume, C. O., Omeje, E. E., and Umeh, O. J. (2025). Small-Scale Farmers' Uptake of Eco-Friendly Vegetable Production Practices in Enugu State, Nigeria. *Journal of Agricultural Extension*, *29*(1), 76-90. https://doi.org/10.4314/jae.v29i1.8

Mahadik, R. V., Pawar, A. S., Navalgund, D. I., Desai, S., Ayarekar, S., and Yadav, J. S. (2025). Bridging Distribution Gaps: A Conceptual Framework for Microinsurance Delivery to Remote Subsistence Farmers. *Enterprise Development and Microfinance*, *35*(1), 188-206. https://papjournals.com/index.php/edm/article/view/15

Wahbi, A., Sarfo, Y., and Musshoff, O. (2023). Female Smallholder Farmers' Preferences for Digital and Conventional Credit Attributes: Evidence from Madagascar. *Agricultural Finance Review*, *83*(4–5), 549–571. https://doi.org/10.1108/AFR-01-2023-0008

Wang, Y., Zhao, Z., and Lu, C. (2024). Does Digital İnclusive Finance İncrease Land Rent? Evidence from Rural China. *Economic Analysis and Policy*, *82*, 1025–1043. https://doi.org/https://doi.org/10.1016/j.eap.2024.04.032

Widjaja, E., Utomo, B. N., Santoso, A. D., Erlambang, Y. P., Surono, Firmansyah, M. A., Handoko, S., Erythrina, E., Rofiq, M. N., Iskandar, D., Sasongko, N. A., Rochmadi, T., Abbas, N., Hanif, M., Garno, Y. S., Arianti, F. D., Suretno, N. D., Askinatin, M., Hastuti, C. O. I., and Fahrodji, F. (2024). Sustainability İndex Analysis for Environmentally Low-İnput İntegrated Farming. *Global Journal of Environmental Science and Management*, *10*(2), 537–556. https://doi.org/10.22034/gjesm.2024.02.08

Zuhri, N. M., Puspita, N., and Aisyah, S. (2024). Efficiency of Corn Cultivation to Enhance Food Self-Sufficiency in Indonesia. *Revista de Ciencias Agroveterinarias*, *23*(4), 616–623. https://doi.org/10.5965/223811712342024616