

DETERMINANTS OF FINANCIAL INCLUSION AMONG SMALLHOLDER FARMERS IN ZIMBABWE

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Abstract. Financial inclusion is critical for improving rural livelihoods, yet many farmers remain excluded due to various socioeconomic and systemic barriers. This study examines the factors influencing financial inclusion among smallholder farmers in Zimbabwe, focusing on access to formal financial services. The study employs a binary logistic regression model to analyze data collected from smallholder farmers, assessing the impact of financial literacy, education, age, gender, household size, and farm characteristics on financial participation. The results indicate that while 94.4% of farmers achieve basic financial inclusion, only 25.6% access multiple financial services. Financial literacy emerges as the most significant determinant, with limited education, large household sizes, and gender disparities having a negative effect. Systemic barriers, including high transaction costs and inadequate rural banking infrastructure, further hinder inclusion. The study highlights the importance of targeted financial literacy programs, gender-sensitive financial products, and improved rural financial infrastructure. Policy recommendations include expanding mobile banking services, reducing transaction costs, and fostering collaboration between financial institutions and policymakers. Future research should assess the long-term impact of financial literacy initiatives and the effectiveness of digital financial services in enhancing inclusion. Increasing financial access could improve the resilience of smallholder farmers, thereby contributing to sustainable agricultural development and economic growth in Zimbabwe.

Keywords: financial access, comprehensive inclusion, financial inclusion, smallholder farmers, Zimbabwe agriculture

INTRODUCTION

Financial inclusion is widely acknowledged as a key driver of economic development, particularly in low- and middle-income countries. Financial inclusion is the process through which individuals and businesses obtain access to useful and affordable financial products and services that meet their needs, provided in a responsible and sustainable manner (World Bank, 2024). It encompasses three critical dimensions – access, usage, and quality – that collectively define the availability of affordable and appropriate financial products and services for individuals and enterprises of all sizes (World Bank, 2024). Access refers to both the presence and affordability of financial services; usage denotes consistent and meaningful engagement with these services; and quality captures the capacity of financial offerings to meet the diverse needs of users (Hasan et al., 2024). Together, these components contribute to financial stability and inclusive economic growth, particularly within the agricultural sector, where smallholder farmers represent a significant portion of the workforce in developing economies.

Smallholder agriculture plays a crucial role in providing food security and supporting economic resilience in many developing nations. Enhancing financial inclusion in this sector can provide farmers with access to essential financial services, including credit, savings, transactions, insurance, and payment systems (Chikweche et al., 2023). These services enable farmers to

Accepted: 20.05.2025

Published: 30.06.2025

Cite as: Masuka, A. (2025). Determinants of financial inclusion among smallholder farmers in Zimbabwe. *J. Agribus. Rural Dev.*, 2(76), 197–206. <http://dx.doi.org/10.17306/J.JARD.2025.00016R2>



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manage their resources effectively, invest in productivity-enhancing activities, and mitigate risks associated with climate change and market fluctuations. Given its role in enhancing resilience and productivity, expanding financial access in the agricultural sector remains a priority.

The concept of financial inclusion gained global attention in 2006, when Muhammad Yunus, the founder of Grameen Bank, received the Nobel Peace Prize for pioneering microfinance (Matsvai, 2024). Since then, financial inclusion has become a central focus of global development, aligning with the United Nations' Sustainable Development Goals (SDGs) and the G20's High-Level Principles for Digital Financial Inclusion (World Bank, 2024). These initiatives emphasize financial access as a catalyst for economic growth and poverty alleviation. Despite progress, financial disparities persist. The World Bank's Global Findex Report (2021) indicates that 76% of adults worldwide now have access to financial services, up from 51% in 2011. However, regional gaps remain – sub-Saharan Africa's financial inclusion rate is 55%, while that for Zimbabwe stands at 50% (FinMark, 2022). Barriers, including a lack of collateral, high transaction costs, weak financial infrastructure, and limited literacy, hinder access to financial services for rural and agricultural communities (Matsvai, 2024).

In smallholder agriculture, financial exclusion is influenced by infrastructure gaps, limited access to agricultural credit, and systemic risks such as climate change and price volatility (Chimanga and Kawimbe, 2024). Gender disparities, low education, and financial illiteracy further restrict access (Matsvai, 2024). Overcoming these challenges requires targeted interventions, including enhanced financial education, expanded rural banking, and innovative financial solutions specifically designed for farmers.

This study examines financial inclusion among Zimbabwean smallholder farmers by assessing their access to essential financial services, including credit, savings, insurance, and payment systems. Following the approach proposed by Sarma (2016), farmers are classified into five levels of financial inclusion – full, comprehensive, partial, basic, and complete exclusion – based on the extent and depth of their engagement with formal financial institutions. Findings from this study will provide policymakers and development practitioners with evidence-based insights to design strategies that enhance

both agricultural sustainability and financial resilience among smallholder farmers. While the relationship between financial inclusion and agricultural sustainability is a central hypothesis of this research, emerging empirical evidence suggests a positive link between the two. For instance, Gao et al. (2022) demonstrate that digital financial inclusion significantly improves agricultural green total factor productivity, highlighting the role of inclusive finance in promoting sustainable agricultural practices. This study aims to inform targeted policies that improve financial access and contribute to sustainable economic development in the agricultural sector by identifying key barriers and drivers in the Zimbabwean context.

OVERVIEW OF FINANCIAL INCLUSION IN ZIMBABWE

Zimbabwe has made progress in financial inclusion, with the Reserve Bank of Zimbabwe (RBZ) reporting that by 2022, 83% of adults were accessing financial services, while 12% remained excluded (RBZ, 2025). Mobile money has significantly improved access, especially in rural areas, yet only 46% of adults use traditional banking services (FinMark, 2022). Gender parity has improved, with equal exclusion rates for men and women (RBZ, 2025); however, smallholder farmers and rural populations continue to face significant barriers, including limited financial literacy, inadequate infrastructure, and restricted access to credit. Less than 40% of smallholder farmers utilize formal financial services, instead relying on informal savings groups and money lenders (World Bank, 2024). Zimbabwe's financial sector comprises formal institutions regulated by the RBZ, mobile financial services under the purview of the Postal

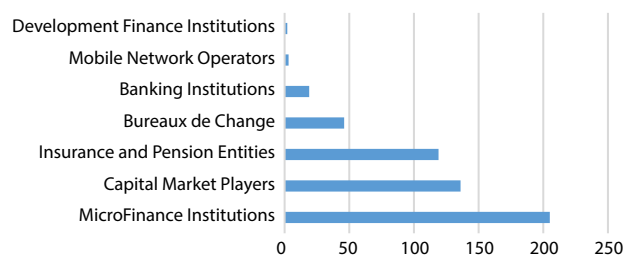


Fig. 1. Zimbabwe's Financial Services Outlook (RBZ, 2025)
Source: own elaboration.

and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ), and informal mechanisms overseen by the Ministry of Women Affairs, Community, Small and Medium Enterprises Development, as shown in Figure 1 below. Expanding financial inclusion requires coordinated efforts among regulators, financial providers, and policymakers to bridge existing gaps.

METHODOLOGY

Data

The study was conducted in nine rural districts of Mashonaland East province in Zimbabwe. A structured questionnaire was developed to collect quantitative data for the research. The Research Ethics Committee of the Agribusiness and Management Department at Marondera University of Agricultural Sciences and Technology (MUASt) approved the structured questionnaire used in this study (Approval Number: MUASt 03/24) in accordance with the MUASt Research Ethics Policy (2020). The primary data sources for this study were smallholder farming households. Data were collected from a sample of 445 households through face-to-face interviews using a structured questionnaire. The first part of the questionnaire aimed to identify the socio-demographic characteristics of the respondents' households. The second part included questions on several broad categories: agricultural status, financial services and products, financial literacy, and household income estimation. The survey questions were adapted from established instruments, including previous household surveys conducted in Zimbabwe and guidelines from the World Bank's Global Findex framework (World Bank, 2024).

The sample unit consisted of household heads who were farmers aged 18 or older, and these individuals were included irrespective of whether they participated in the official financial market. The sample size for the household survey was calculated using a derivative of Yamane's formula for calculating sample size when population size is finite (Sorzano, 2022). Given that the total number of households in the nine rural districts of Mashonaland East based on the 2022 population census is 392,724 (ZIMSTAT, 2022), aiming for a 95% confidence level and a 5% margin of error, and assuming that the attribute proportion is 0.5, the sample size for the household survey was 445. The sample sizes per district were distributed proportionally. The strategy for sampling respondents involved random selection of

villages within each ward, followed by systematic sampling of five participants per village. Leaders from the village assisted in selecting farming households to be respondents. The study primarily relied on the Lot Quality Assurance Sampling (LQAS) technique (Kamau et al., 2024). Using the LQAS, 24 wards were selected to represent the various agro-ecological zones in the province for the study.

Methods of Analysis

This study employs quantitative methods, including descriptive analysis, inferential statistics, and binary logistic regression, to investigate the factors influencing smallholder farmers' access to financial services. The analysis models financial inclusion or exclusion based on four main variables: agricultural credit, savings accounts, insurance and mobile money wallets.

Model Specification

The binary logistic regression model was chosen due to the dichotomous nature of the dependent variable. Financial inclusion was assigned a value of 1 (included), and financial exclusion was assigned a value of 0 (excluded). This method assumes the dependent variable follows a Bernoulli distribution dependent on predictor variables (Fritz and Berger, 2015). Let P_j represent the probability that the j^{th} farmer is formally financially included, and assuming that P_j is a Bernoulli random variable and its distribution depends on the predictor vector X , then:

$$P_j(X) = \frac{e^{\alpha + \beta X}}{1 + e^{\alpha + \beta X}} \quad (1)$$

The logit function to be estimated is then expressed as:

$$\ln\left(\frac{P_j}{1 - P_j}\right) = \alpha + \sum I\beta_i X_{ij} \quad (2)$$

Where the logit variable $\left(\frac{P_j}{1 - P_j}\right)$ represents the natural logarithm of the odds favouring a farmer being formally financially included. The coefficient estimates of β indicate the change in the log-odds (the logarithm of relative probabilities) of the outcome, here equal to 1, for a one-unit increase in the independent variable, while holding all other independent variables constant. Logit regressions are calculated using Maximum Likelihood

Estimation (MLE) instead of Ordinary Least Squares (OLS) (Vaibhav, 2023). MLE computes coefficient estimates that maximize the likelihood of the sample data set being observed.

The use of Maximum Likelihood Estimation (MLE) in binary logistic regression is particularly appropriate due to the categorical nature of the dependent variable, which is dichotomous – farmers are either financially included (1) or excluded (0). Ordinary Least Squares (OLS) is designed for continuous dependent variables and assumes that errors are normally distributed and homoscedastic – assumptions which do not hold in the context of binary outcomes (Fritz and Berger, 2015). Applying OLS to a binary dependent variable can result in predicted probabilities outside the [0,1] interval and inefficient, biased parameter estimates. In contrast, MLE is robust to these limitations, as it directly estimates parameters by maximizing the probability of observing the actual outcomes in the data, given the model's predictors. This approach produces consistent, efficient, and asymptotically normal estimates, making it the preferred estimation technique for logistic regression models used to analyze financial inclusion and other binary choice phenomena (Fritz and Berger, 2015; Vaibhav, 2023).

The binary logistic regression model is specified as follows:

$$C_{ij} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + X_{1-X_{15}} \quad (3)$$

Where:

C_{ij} – is the probability of financial inclusion (dummy = 1 if a farmer is formally financially included, and 0 if financially excluded)

β_0 – is the intercept and β_1 – β_{15} are the coefficients for the independent variables X_1 – X_{15}

X_1 – X_{15} – are the independent variables (age of the household head, gender of the household head, household head's level of education, household head's employment status, annual income, smartphone ownership, financial literacy, access to financial services, financial market proximity, ICT device ownership, mobile network connectivity, internet access, attitude towards risk, extension contact, and membership in farmer organization)

$X_{1-X_{15}}$ – is the stochastic error term

k – is the number of independent variables (predictors) included in the model.

Following the multidimensional framework proposed by Sarma (2016), financial inclusion in this study is categorized into five levels based on a farmer's access to formal financial services: fully included (4) – access to credit, savings, insurance, and mobile money; comprehensively included (3) – access to three of the four services; partially included (2) – access to two services; basic inclusion (1) – access to one service; and excluded (0) – no access to formal financial services.

EMPIRICAL RESULTS AND DISCUSSION

This study examines the factors influencing financial inclusion among Zimbabwean smallholder farmers, focusing on their access to formal financial services. Data from 445 farmers in Mashonaland East were analyzed using various statistical methods to identify key predictors of financial inclusion.

Descriptive Statistics

Summary of socioeconomic and financial characteristics of smallholder farming households

Table 1 displays the descriptive statistics for the variables utilized in this study.

Key demographic and socioeconomic factors influencing financial inclusion include education, employment, ICT ownership, and income. Most farmers have basic financial access, but disparities persist. This aligns with the findings of Hasan et al. (2024), who reported that mobile banking in rural areas significantly enhances financial inclusion. The average education level is 4.10, indicating that most farmers have completed secondary education. The positive skewness of 0.37 indicates that most smallholder farmers have primary or secondary education, while the low kurtosis of 1.94 suggests that there is no extreme variation in educational attainment. Informal employment (mean = 1.58) limits access to financial services, as institutions typically require proof of stable income (Osabutey and Jackson, 2024).

ICT device ownership is high (mean = 1.96), indicating near-universal mobile phone usage, which presents an opportunity for mobile banking expansion. However, participation in savings groups remains low (mean = 0.13), which limits the potential for financial inclusion. The average age of household heads is 45.38 years (SD = 12.73), indicating a slight positive skewness (0.30) that suggests a somewhat younger population

Table 1. Summary statistics for the variables ($n = 445$)

Variable name	Observations	Mean	Std. dev.	Variance	Skewness	Kurtosis
Financial inclusion	445	0.950562	0.217025	0.0471	−4.15684	18.27928
Age of the household head	441	45.38209	12.73353	162.1429	0.300476	2.745366
Highest education level	441	4.099773	2.443735	5.971841	0.36687	1.945309
Employment status	441	1.578231	1.030833	1.062616	0.337922	1.733848
Annual income	441	239.3197	414.9766	172205.6	3.448793	17.75139
Financial literacy	445	0.262921	0.811292	0.658194	−0.10808	2.181049
ICT device ownership	441	1.959184	0.198089	0.039239	−4.6414	22.54255
Distance to financial institution	441	41.44898	35.63282	1269.698	8.492423	129.4015
Membership of savings group	445	0.134832	0.341928	0.116915	2.138843	5.572511

Std. dev. – standard deviation.

Source: own estimation.

distribution, with financial literacy generally increasing with age. Younger farmers struggle with access due to limited collateral. Income disparities are pronounced (mean = USD 239.32, SD = USD 414.98, skewness = 3.45), reflecting considerable income inequality, and this underscores the need for subsidized credit programs for low-income farmers. The distance to financial institutions (mean = 41.45 km, SD = 1,269.70) highlights accessibility challenges, reinforcing the need for mobile banking. Studies by Chikweche et al. (2023) and Chandio et al. (2021) corroborate the role of these variables in enhancing financial inclusion.

Access to financial services by smallholder farmers

Table 2 below presents the distribution of smallholder farmers based on the types of financial services they

accessed. The data reflect utilization patterns across savings, credit, insurance, and mobile money services.

Basic access to at least one financial service is high, at 94.4%, with mobile banking leading the adoption, a trend that mirrors those in Mozambique and Kenya (Tiwasang et al., 2024). However, only 26.9% engage in formal savings, hindered by low income and distrust of banks (Dzingirai et al., 2024). Informal savings appear to be the dominant form due to economic, financial, and social considerations. Agricultural credit access is low (20.1%), primarily due to high collateral requirements and risk aversion. This finding is consistent with prior research by Mushore and Makate (2022), which identifies credit constraints as a significant obstacle to financial inclusion for smallholder farmers in sub-Saharan Africa. Even fewer farmers (13.4%) use agricultural

Table 2. Distribution of smallholder farmers by type of financial services accessed (Nominal variables, $n = 445$)

Financial service	Frequencies (number of respondents)	Percentage (%)
Mobile money (payment systems)	150	33.6
Savings	120	26.9
Agricultural credit	90	20.1
Agricultural insurance	60	13.4
No services accessed	25	5.6

Source: own compilation.

insurance due to affordability and awareness issues. A small segment (5.6%) remains financially excluded due to economic hardship and distrust, aligning with the results of a study by Chimwai (2022), which found that a significant portion of Zimbabwe's informal sector population remains financially excluded. Mobile banking and microfinance could bridge this gap.

Extent of financial inclusion among smallholder farmers

Assessing the depth of financial inclusion provides a clearer understanding of its impact. According to the World Bank (2025), it is not enough for individuals to access a single financial service; they must actively use various services to enhance their livelihoods. This study employs an adaptation of Sarma's (2016) composite financial inclusion index (FI-Index) to categorize farmers into five levels: completely excluded, basic, partial, comprehensive, and full inclusion. Table 3 presents the distribution of financial inclusion and exclusion.

Middle-aged farmers have the highest financial access, while young adults (18–35) and the elderly (60+) struggle due to factors such as low income, limited access to financial products, and, in the case of older individuals, digital illiteracy (Khan et al., 2021). Gender disparities persist, with men experiencing greater financial inclusion while women face systemic barriers, such as restricted land ownership and lower literacy levels. Financial inclusion increases significantly with education, increasing from 35.6% among those with only primary schooling to 68.4% among those with tertiary qualifications. Employment status is also crucial, as unemployed farmers face 71.1% exclusion. Higher-income farmers (75.9%) enjoy greater financial access. These results are consistent with earlier studies conducted across Africa, particularly those by Gan et al. (2022) and Ansar et al. (2023), which focused on assessments of rural financial inclusion.

The study adapts metrics from Sarma (2016) to measure financial inclusion across categories: basic, partial, comprehensive, full, and completely excluded. The results are shown in Table 4.

Overall, at least basic inclusion is attained by 94.38% of farmers, while only 25.62% achieve meaningful financial inclusion (comprehensive and full), as defined by the G20's Basic Set of Financial Inclusion Indicators (GPFI, 2012). This pattern suggests that although a notable proportion of smallholder farmers have some access to financial services, many still face obstacles to

Table 3. Financial inclusion across demographics and socio-economic variables ($n = 445$)

Category	Financially included (%)	Financially excluded (%)
Age 18–35	45.2	54.8
Age 36–60	55.8	44.2
Age above 60	32.1	67.9
Gender – Male	60.4	39.6
Gender – Female	48.7	51.3
Primary education level	35.6	64.4
Secondary education level	50.2	49.8
Tertiary education level	68.4	31.6
Employment status (Unemployed)	28.9	71.1
Employment status (Self-employed)	55.1	44.9
Employment status (Employed)	72.3	27.7
Income level (Low)	30.5	69.5
Income level (Medium)	55.7	44.3
Income level (High)	75.9	24.1

Note: “Financially included” refers to individuals accessing at least one formal or informal financial service (savings, credit, insurance, or mobile money). “Financially excluded” refers to individuals with no access to any financial services.

Source: authors' analysis of household survey data.

Table 4. Financial inclusion by levels ($n = 445$)

Financial level	Frequency	Percentage
Completely excluded	25	5.62
Basic	150	33.71
Partial	156	35.06
Comprehensive	88	19.78
Full	26	5.84

Source: own compilation.

achieving full integration into the formal financial system. The FinScope Zimbabwe 2022 Consumer Survey supports these findings, reporting that formal financial inclusion increased from 38% in 2011 to 84% in 2022.

However, only 27% of rural adults utilized formal financial services, highlighting a substantial reliance on informal financial practices, such as home savings and informal lending sources (FinMark, 2022). This highlights that despite significant progress in financial inclusion, a large portion of the population, especially smallholder farmers, remains underserved or excluded from the formal financial system. Addressing these issues requires targeted interventions, such as enhancing rural financial infrastructure, reducing transaction costs, and expanding financial literacy programs.

Econometric Results

Table 5 below summarizes key metrics from the goodness-of-fit test. The logistic regression model's log-likelihood (−51.1589), LR chi-square (25.14, $p < 0.0001$), and pseudo-R-squared (0.1972) indicate reasonable explanatory power. The model accuracy is high (94.75%), with strong sensitivity (99.68%) but poor specificity (0.00%), indicating limitations in classifying excluded cases.

The regression model in Table 6 estimates the key determinants of financial inclusion among smallholder farmers. The likelihood ratio chi-square test (LR $\chi^2(9)$

= 77.09, $p < 0.001$) confirms that the overall model is statistically significant, indicating that at least one predictor has a meaningful effect on financial inclusion.

Financial literacy has a significant positive effect on financial inclusion ($\beta = 0.8794$, $p < 0.001$), supporting findings by Osabutey and Jackson (2024) and Matsvai (2024), who emphasized the role of literacy in improving access to credit and formal financial services. Distance from financial markets also has a significant negative effect ($\beta = -0.0283$, $p < 0.001$), suggesting that greater distances discourage inclusion. Membership of savings groups is negatively associated with basic financial inclusion ($\beta = -0.9024$, $p = 0.035$), possibly reflecting reliance on informal mechanisms over formal services. While variables such as age, education, household size, and farm size showed marginal significance ($p < 0.10$), farm size, introduced as a new variable to reflect economic potential, was not statistically significant ($\beta = 0.0058$, $p = 0.118$). ICT device ownership was omitted from the model due to a lack of variability, as nearly all respondents reported owning mobile phones. These findings reinforce the importance of targeted financial literacy programs and improved physical

Table 5. Metrics from the goodness of fit test

Classification confusion matrix and performance metrics				Goodness-of-fit test	
Classified	– True –		Total	Statistic	Value
	D	~D			
+	307	16	323	Number of Observations	324
–	1	0	1	Number of Covariate Patterns	313
Total	308	16	324	Pearson Chi-square (chi2(299))	239.90
Sensitivity	Pr (+ D)		99.68%	Prob > chi2	0.9982
Specificity	Pr (– ~D)		0.00%		
Positive Predictive Value	Pr (D +)		95.05%		
Negative Predictive Value	Pr (~D –)		0.00%		
False + rate for true ~D	Pr (+ ~D)		100.00%		
False – rate for true D	Pr (– D)		0.32%		
False + rate for classified +	Pr (~D +)		4.95%		
False – rate for classified –	Pr (D –)		100.00%		
Correctly classified	94.75%				

Source: own analysis based on household survey data.

Table 6. Results of the logistic regression model on determinants of basic financial inclusion

Variable	Coefficient	Std. error	z-value	P> z	95% Confidence Interval
Financial literacy	0.8794	0.198	4.44	< 0.001	[0.4913, 1.2676]
Age category	0.1882	0.1182	1.59	0.111	[−0.0436, 0.4199]
Financial market proximity (km)	−0.0283	0.0071	−4.02	< 0.001	[−0.0422, −0.0145]
Highest education level attained	−0.1052	0.0596	−1.76	0.078	[−0.2221, 0.0117]
Household size	0.1078	0.0618	1.74	0.081	[−0.0133, 0.2290]
Farm size (ha)	0.0058	0.0037	1.56	0.118	[−0.0015, 0.0130]
ICT device ownership	Omitted	–	–	–	–
Employment status	0.0549	0.1418	0.39	0.698	[−0.2230, 0.3328]
Mobile network connectivity	−0.2176	0.6193	−0.35	0.725	[−1.4315, 0.9963]
Membership of savings group	−0.9024	0.4277	−2.11	0.035	[−1.7407, −0.0641]
Constant (cons)	−0.6431	0.8916	−0.72	0.471	[−2.3905, 1.1044]

Number of observations = -311; Log likelihood = -158.94504; LR $\chi^2(9) = 77.09$; Pseudo $R^2 = 0.1952$; Prob > $\chi^2 = < 0.00$.

Source: own analysis based on household survey data ($n = 311$).

access to financial services to enhance inclusion among rural farming communities.

CONCLUSIONS AND RECOMMENDATIONS

Financial inclusion among smallholder farmers in Zimbabwe remains a challenge despite some progress in providing access to financial services. This study examined the determinants and extent of financial inclusion among smallholder farmers in Mashonaland East province, Zimbabwe, using data from 445 households. The results reveal that although basic access to at least one financial service is relatively high (94.4%), meaningful inclusion remains limited. Only 25.6% of respondents achieved meaningful financial inclusion (comprehensive and full), underscoring the gap between formal service access and actual, diversified financial engagement. Mobile money services emerged as the most widely used. At the same time, access to savings, credit, and agricultural insurance remains low due to barriers such as high collateral requirements, limited financial literacy, and lack of trust in formal institutions.

The logistic regression analysis highlights financial literacy as the most significant and positive predictor of financial inclusion. Farmers with greater financial

understanding are more likely to access a variety of financial services, affirming the importance of knowledge in navigating formal financial systems. Conversely, physical distance to financial institutions significantly hampers access, with each additional kilometre reducing the likelihood of inclusion. This finding demonstrates the ongoing challenge of rural financial infrastructure in Zimbabwe. Additionally, membership in informal savings groups shows a significant negative association with basic financial inclusion, suggesting that these groups may serve more as substitutes than as pathways to formal financial systems.

Other variables, such as education level, household size, and farm size, exhibited marginal statistical significance, while employment status and mobile connectivity did not show significant effects. Interestingly, ICT ownership was omitted for uniformity, as most farmers owned mobile phones. This highlights the potential for mobile financial services but also indicates the need to address other structural limitations that prevent service use. The findings suggest that while access to digital tools exists, usage of financial services depends on broader economic, educational, and institutional factors.

The data further reveal disparities in financial inclusion across age, gender, income, and employment categories. Younger and older farmers, women, and those

with low-income or unstable employment are more likely to be excluded, reinforcing the role of structural inequalities and economic vulnerability. These patterns echo regional findings and point to the multidimensional nature of financial inclusion.

Several targeted interventions are recommended to address these gaps. First, scaling up financial literacy programs tailored to rural populations and vulnerable groups like youth and women can empower farmers to make informed financial decisions. Second, expanding mobile and agent-based financial services can help overcome the physical barriers posed by distance to brick-and-mortar institutions. Policymakers should incentivize telecoms and financial providers to extend services to underserved areas.

Third, developing inclusive financial products, such as low-collateral loans, bundled services, and gender-responsive financial solutions, can broaden access and usage. Stronger collaboration among the Reserve Bank of Zimbabwe, financial institutions, development partners, and community organizations is critical for a sustained impact. Finally, ongoing monitoring and research are essential to assess the effectiveness of these interventions and to adapt strategies to emerging needs.

In conclusion, improving financial inclusion for smallholder farmers necessitates increasing access to financial services and addressing systemic, behavioural, and infrastructural barriers. This approach is crucial for building resilience in rural areas, enhancing productivity, and promoting inclusive agricultural and economic development in Zimbabwe.

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