S. Afr. J. Agric. Ext. Shemfe & Modirwa
Vol. 54 No. 1, 2026: 190-223
10.17159/2413-3221/2026/v54n1a20927

Barriers to the Adoption of Information and Communication Technology (ICT) for Accessing Agricultural Information by Small-Scale Farmers in Mahikeng, Northwest Province

Shemfe, O.[1] and Modirwa, S.[2]

Corresponding Author: O. Shemfe. Correspondence Email: olaitanshemfe86@gmail.com

ABSTRACT

Small-scale farmers in Mahikeng, South Africa, face significant challenges in leveraging Information and Communication Technology (ICT) for agricultural information. This study examined how socio-economic characteristics and perceived barriers influence the adoption of ICT. A cross-sectional survey of 121 farmers was conducted using a structured, pre-tested questionnaire, and data were analysed using descriptive statistics and binary logistic regression. Findings showed that while 92% of respondents were aware of ICT-based agricultural services, actual adoption was uneven. Approximately 86% used ICT, primarily radios and mobile phones, while internet-based platforms were relatively rare. Barriers were multifaceted, with unreliable electricity and poor connectivity being the most frequently cited (85%), followed by high device costs (71%) and unaffordable data (73%). The absence of local ICT hubs (79%) and socio-cultural constraints such as low literacy and language mismatches further limited uptake. Regression analysis revealed that larger farm sizes significantly increased the likelihood of adoption, while high perceived costs and poor internet access reduced it. Overall, despite high awareness, ICT adoption is constrained by intersecting infrastructural, economic, and socio-cultural barriers. Addressing these issues requires a holistic strategy that combines infrastructure investment, affordability interventions, and targeted digital literacy support.

Keywords: ICT Adoption, Small-Scale Farmers, Barriers.

[1] Post-Doctoral Research Fellow: Department of Economics and Business Management. Faculty of Economics and Financial Sciences, Walter Sisulu University, South Africa. olaitanshemfe86@gmail.com, ORCID ID: 0000-0003-0996-1505.

[2] Senior Lecturer: Department of Agricultural Economics and Extension. Faculty of Natural and Agricultural Sciences, Northwest University, South Africa. Sinah.Modirwa@nwu.ac.za, ORCID ID: 0000-0001-5431-4871.

1. INTRODUCTION

In the modern agricultural landscape, access to timely and relevant information plays a crucial role in enhancing productivity and sustainability, particularly for small-scale farmers. Information and Communication Technology (ICT) has the potential to bridge knowledge gaps by providing access to vital agricultural information on weather patterns, market prices, pest management, and improved farming techniques (Choruma, 2024; Domguia, 2025). For small-scale farmers who often face resource constraints, ICT offers opportunities to enhance yields, mitigate risks, and increase profitability (Ngulube, 2025; Onyeneke *et al*., 2023). In the context of this study, ICT refers to technologies such as mobile phones, radio, television, computers, and internet services that facilitate the dissemination and exchange of information. The term agricultural information encompasses any knowledge that supports farming decision-making, including data on weather forecasts, input and output market trends, pest and disease management, and improved farming practices.

However, despite its potential, many small-scale farmers in Mahikeng Local Municipality (like those in other regions of sub-Saharan Africa) face significant barriers to adopting ICT. These challenges include limited access to digital infrastructure, low levels of digital literacy, language and educational constraints, and economic hardships, all of which hinder farmers' ability to fully benefit from agricultural information systems (Nxumalo, 2025; Smidt & Jokonya, 2022; Oki & Agbeyangi, 2024). Previous studies have revealed such constraints in broader contexts, but there remains a need to understand the specific severity and interplay of these barriers in Mahikeng. In other words, although it is recognised that inadequate infrastructure, restricted device access, low digital skills, and high internet costs impede ICT uptake (Ayim et al., 2020; Fox & Signe, 2022), the extent of these problems and how they relate to farmers' characteristics in this area have not been thoroughly documented. This represents a critical knowledge gap. Consequently, small-scale farmers in Mahikeng continue to struggle with accessing important agricultural information, making them more vulnerable to climate shocks, price fluctuations, and pest outbreaks. There is a clear problem: ICT-based services that could mitigate these risks are underutilised, and the local farming community remains less informed and less resilient than it could be. Addressing these obstacles is crucial for improving ICT adoption, promoting informed agricultural practices, and bolstering the livelihoods of small-scale farmers in the area.

1.2. Research Aim, Objectives and Hypothesis

Considering the persistent challenges faced by small-scale farmers in accessing critical agricultural information, this study seeks to explore the factors influencing their adoption of ICT tools in the Mahikeng Local Municipality. While ICT has the potential to bridge information gaps and improve farming outcomes, its uptake remains limited, often constrained by infrastructural, educational, and economic barriers. To better understand this underutilisation, the study focuses on how socio-economic characteristics and perceived barriers shape farmers' likelihood of adopting ICT for agricultural purposes.

The overall aim of this research is to examine how the socio-economic profiles of small-scale farmers and their perceived barriers influence their adoption of ICT tools for accessing agricultural information. Specifically, the study identifies whether farmers have adopted ICT (based on a binary yes/no response), identifies the types of barriers they face, and assesses how these barriers, together with socio-economic characteristics, predict ICT adoption. A binary logistic regression model is used to determine which factors are significantly associated with ICT uptake, providing insights to guide future policy and support interventions aimed at increasing digital inclusion in the agricultural sector.

The following hypotheses were tested in this study:

Null Hypothesis (H_0): There is no significant relationship between small-scale farmers' socio-economic characteristics and perceived barriers, and their adoption of ICT for accessing agricultural information.

Alternative Hypothesis (H_1): There is a significant relationship between the socio-economic characteristics of small-scale farmers and their perceived barriers to adoption, as well as their use of ICT for accessing agricultural information.

2. METHODOLOGY

2.1. Study Area

Located in South Africa's Northwest Province, Mahikeng Local Municipality spans approximately 3,703 km² and comprises 28 wards and over 100 villages, accommodating a population estimated between 270,000 and 350,000 (Mahikeng Local Municipality, 2024; Municipalities of South Africa, 2024). Approximately 70% of the municipality is classified as rural, with over 40 scattered villages situated as far as 120 km from the urban core

(Municipalities of South Africa, 2024). Despite a high rate of household electrification (97%), access to essential services such as piped water and flush sanitation remains limited, reaching only about half of the population (Municipalities of South Africa, 2024). The municipality also faces significant socio-economic challenges, including a 35.7% unemployment rate and a predominantly young population with modest educational attainment levels. Only 26% hold a matric certificate, while 7% have received no formal education (Municipalities of South Africa, 2024).

Agriculture remains a cornerstone of Mahikeng's economy, with a focus on livestock, particularly cattle, sheep, and goats, as well as crops such as maize and sunflowers. However, the sector is highly susceptible to drought (Setshedi & Modirwa, 2020). While Mahikeng, alongside its main suburb Mmabatho, functions as the administrative and commercial nucleus, many peripheral villages still lack adequate infrastructure and service delivery (Mahikeng Local Municipality, 2024). Strategically situated near the Botswana border and key transportation routes leading to Gauteng, the municipality holds untapped potential for enhanced market access and digital connectivity.

Mahikeng was chosen as the focus of this study owing to its substantial population of smallholder farmers facing socio-economic hardship, coupled with recent governmental agricultural initiatives. For instance, the Northwest Department of Agriculture and Rural Development (DARD) has constructed a modern livestock-handling facility in Ditshilo village and supported community gardening efforts in Ottoshoop as part of the Thuntsha Lerole food security initiative. Additionally, a farmer in Setlopo was provided with Boer goat breeding stock through departmental support (Food for Mzansi, 2024; Northwest DARD, 2024).

2.2. Research Design

This study employed a descriptive quantitative research design to investigate the barriers to the adoption of Information and Communication Technology (ICT) for accessing agricultural information by small-scale farmers in Mahikeng Local Municipality, Northwest Province. A descriptive design was considered appropriate as it facilitates an in-depth understanding of prevailing conditions and the identification of key trends among a specific population (Creswell & Creswell, 2018). Quantitative methodology was applied to systematically collect and analyse numerical data related to socio-economic characteristics, ICT usage, and perceived barriers. This approach allowed for objectivity, replicability, and the use of inferential statistics to test the relationships between variables (Mohajan, 2021). The design further enabled the evaluation of farmers' ICT adoption patterns, supported by structured and standardised data collection and analysis processes.

Given the aim of determining the influence of socio-economic characteristics and barriers on ICT adoption, the study applied a cross-sectional survey design, capturing data from a sample of small-scale farmers at a single point in time. This approach ensured a representative snapshot of current ICT adoption behaviours and constraints within the study area.

A binary logistic regression model was selected as the core statistical method to test the null hypothesis: There is no significant relationship between the socio-economic characteristics of small-scale farmers and their barriers to adopting ICT for accessing agricultural information. This model was suitable because the dependent variable, ICT adoption, was binary (1 = adopter, 0 = non-adopter), and the predictor variables included both continuous (e.g., farm size) and categorical factors (e.g., cost of ICT tools, digital infrastructure, literacy level). To ensure the validity of the model, multicollinearity was assessed using the Variance Inflation Factor (VIF) and Tolerance values. All tested variables met the acceptable thresholds (VIF < 10, Tolerance > 0.1), confirming the reliability of the regression outputs. The model's goodness-of-fit was confirmed with a statistically significant LR chi^2 value ($p < 0.0000$) and a strong Pseudo R^2 of 0.6568, indicating that the model explained a substantial proportion of variance in ICT adoption.

2.3. Population of the Study

The target population for this study consisted of all small-scale farmers residing within the designated area of the Mahikeng Local Municipality. Based on official records provided by the Mahikeng Agricultural Office under the Northwest Department of Agriculture and Rural Development (NWDARD), the total number of registered smallholder farmers, encompassing both livestock and crop producers, was 1,449. This figure was adopted as the definitive population frame for the research. A random sampling technique was subsequently employed to select participants from this population. The use of a comprehensive, government-verified registry ensured that the sampling frame was both accurate and representative of the broader smallholder farming community, thereby aligning with the study's descriptive and quantitative research design.

2.4. Sampling Procedure and Sample Size

The sample size was determined using a standard sample size table by Krejcie and Morgan (1970). For a population of around 1,449, this table recommends a sample of about 302 respondents for a 95% confidence level and a 5% margin of error (assuming a proportion of 0.5). In line with this guidance, a target sample of 302 small-scale farmers was considered sufficient to yield statistically meaningful results. In line with this guidance, a target sample of 302 small-scale farmers was considered sufficient to yield statistically meaningful results. A simple random sampling technique was then employed to select participants, ensuring that every farmer in the population had an equal chance of being included. Ultimately, due to practical considerations and voluntary participation, 121 respondents were successfully reached and agreed to participate in the survey. Although the realised sample size is smaller than the initial target, it still provides valuable insights. Bartlett *et al*. (2001) emphasise the importance of considering expected response rates when determining adequate sample sizes in voluntary survey research. Considering this, the 40% response rate achieved in the present study falls within generally acceptable thresholds.

2.5. Data Collection

Data were collected using a structured questionnaire administered in person. The instrument was designed in two sections. The first section gathered data on the socio-economic characteristics of the farmers (e.g., age, gender, education level, farm size, farming experience, household income) and assessed farmers' awareness of ICT in agricultural extension service delivery. The second section focused on the barriers faced by farmers in utilising ICT for agricultural purposes. Respondents were asked about various potential barriers (such as cost, infrastructure, skills, etc.), usually by rating each factor as a "major barrier," "minor barrier," or "not a barrier" in their farming activities. The questionnaires were distributed and self-administered by the researcher, and an extension officer was present to clarify any questions. This approach helped ensure clarity and consistency in data collection. Farmers' responses about barriers were later categorised based on the severity of the barrier (major vs. minor) for analysis.

TABLE 1: Descriptions of Variable, Measurement and Expected Outcomes

Variable	Type	Coding / Measurement	Expected Effect on ICT Adoption
ICT Adoption (DV)	Binary	1 = Yes, 0 = No	Outcome variable
Age	Categorical/ordinal	Farmer's age in years	Negative or neutral
Education Level	Ordinal	1 = No schooling to 5 = Tertiary	Positive
Farm Size	Continuous	In hectares	Positive
Income Level	Ordinal / categorical	Grouped Annual income (e.g., R10,000–R30,000, etc.)	Positive
Gender	Binary	1 = Male, 0 = Female	Neutral or slightly positive
Barrier: Cost of ICT	Binary	1 = Major barrier, 0 = Not major	Negative
Barrier: Poor Network Access	Binary	1 = Major barrier, 0 = Not major	Negative
Barrier: Low Digital Skills	Binary	1 = Major barrier, 0 = Not major	Negative
Barrier: Language or Literacy	Binary	1 = Major barrier, 0 = Not major	Negative

2.6. Justification for the Selection of Variables

The choice of variables for this study is informed by both theoretical and empirical literature rooted in agricultural extension, particularly the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM). DOI suggests that socio-economic characteristics, such as age, education, and income, significantly influence the rate of innovation uptake by affecting the perceived advantages, compatibility, and complexity of the innovation (Rogers, 2003). TAM further emphasises that perceived usefulness and ease of use determine technology acceptance (Davis, 1989), both of which can be shaped by the farmer's resources, skills, and contextual barriers.

Age was included because younger farmers tend to adopt digital innovations more readily than older counterparts, who may perceive such tools as complex or less relevant (Hoang & Tran, 2023). Education level was considered due to its role in enhancing digital literacy and the ability to engage with new technologies, which is well-supported in the literature (Fharaz *et al*., 2022). Similarly, income level and farm size were included based on their positive association with adoption; farmers with greater financial resources or larger operations are often better positioned to invest in ICT tools and data costs (Singh & Aryal, 2023).

Gender was included to account for structural disparities in access to training and digital tools, although evidence on its effect remains mixed and context-dependent (Peterman *et al*., 2014). In addition to these socio-economic factors, the model includes key barriers identified in prior research. High ICT costs, poor network access, low digital skills, and language or literacy constraints are well-documented inhibitors of adoption in African farming contexts (Mhlanga & Ndhlovu, 2023; Awuor & Rambim, 2022). These barriers reduce both the perceived ease of use and usefulness of ICTs, aligning closely with TAM's conceptual framework. Including them as binary variables allows the model to capture their marginal effects on ICT adoption.

2.7. Validity and Reliability

To ensure the content validity of the questionnaire, a face validation process was conducted by a panel of subject-matter experts in Agricultural Extension and Development Studies. The panel comprised a Senior Lecturer in Agricultural Extension, senior officials from the Northwest Department of Agriculture and Rural Development (NWDRAD), as well as experienced researchers with relevant domain expertise. Following this, the instrument was piloted with a purposive sample of 12 small-scale farmers from Mahikeng, selected based on their availability and willingness to participate. These participants were excluded from the main study to prevent bias. Feedback from the pilot exercise informed several revisions, including the rephrasing of ambiguous items, restructuring certain questions, and standardising response scales. These modifications enhanced the clarity, internal coherence, and contextual appropriateness of the instrument for the target population. The reliability of the 9-item Likert scale measuring barriers to ICT adoption was assessed using Cronbach's alpha, which yielded a value of 0.89, indicating high internal consistency. The mean total scale score was 22.85 (SD = 4.38). Inter-item correlations ranged from 0.13 to 0.83, and item-total correlations ranged from 0.32 to 0.73. Deleting any single item reduced Cronbach's alpha to a minimum of 0.87, suggesting that all items contributed meaningfully to the scale.

TABLE 2: Cronbach's Alpha Reliability Statistics for the Barriers Scale

Statistic	Value
Number of items	9
Cronbach's alpha (α)	0.886
Mean of total scale score	22.85
Standard deviation of the total scale score	4.38
Inter-item correlation (range)	0.13 to 0.83
Item-total correlation (range)	0.41 to 0.75
Lowest alpha if item deleted	0.863

2.8. Data Analysis

The collected data were coded and analysed using the Statistical Package for the Social Sciences (SPSS) software. Descriptive statistics (frequencies, percentages, means, and standard deviations) were used to summarise the socio-economic characteristics of the respondents and the prevalence of each barrier to ICT use. The results of these descriptive analyses are presented in tabular form (see Tables 1 and 2) for clarity and ease of interpretation.

To address the hypothesis concerning relationships between farmer characteristics and ICT adoption barriers, a binary logistic regression model was employed. In this model, the dependent variable was ICT adoption status, defined as whether a farmer was actively using any ICT tools to access agricultural information (adopter = 1 if the farmer used at least one ICT platform such as a mobile phone, radio, or internet for farm information; non-adopter = 0 if the farmer did not use any ICT for this purpose). The independent variables included key socio-economic factors (such as farm size, age, education, and income) and the presence of major constraints (e.g., whether the farmer indicated that high costs and lack of internet were a major barrier for them). We coded each potential barrier as 1 if the respondent perceived it as a major constraint and 0 if it was a minor or no constraint. This coding collapses the original three-category constraint scale into a binary indicator focusing on major hindrances (while excluding the "no constraint" category from the analysis as a baseline). The logistic regression thus allowed us to assess which factors significantly influenced the likelihood of a farmer adopting ICT.

Before running the logistic regression, multicollinearity diagnostics were performed to ensure that the predictor variables were not excessively correlated with each other, which could distort the regression results. Variance Inflation Factors (VIF) and tolerance values were examined for all independent variables. All VIF values were below the commonly accepted threshold (e.g., VIF < 5), indicating that multicollinearity was not an issue in the model. After confirming the validity of the predictors, the logistic model was implemented, and the results (coefficients, standard errors, and significance levels) were interpreted in relation to the study objectives**.**

2.9. Binary Logistic Regression Model and Assumptions

The binary logistic regression model used to estimate the probability of ICT adoption among small-scale farmers can be expressed as follows:

$\log(P(Y=1) / (1 - P(Y=1))) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_k X_k$

Where:

$\log(P(Y=1) / (1 - P(Y=1)))$ is the log-odds of being an ICT adopter (i.e., using at least one ICT tool for agricultural information).

$Y = 1$ indicates an ICT adopter, and $Y = 0$ indicates a non-adopter.

β_0 is the intercept.

$\beta_1, \beta_2, ..., \beta_k$ are the coefficients of the independent variables.

$X_1, X_2, ..., X_k$ are the predictor variables.

2.10. Model Fit and Limitations

The overall fit of the logistic regression model was assessed using several standard indicators. The Likelihood Ratio Chi-Square test yielded a statistically significant result (LR $\chi^2 = 64.51$, $p < 0.001$), indicating that the model was statistically meaningful in predicting ICT adoption among small-scale farmers. The log-likelihood value was -16.85, suggesting good model convergence. Additionally, the pseudo-R^2 (McFadden's R^2) value was 0.6568, indicating that approximately 65.7% of the variation in ICT adoption could be explained by the independent variables included in the model. The final model included 121 observations. These results suggest a reasonably strong model fit for binary logistic regression in the context of socio-economic and barrier-related predictors.

While the logistic regression model provided a good fit and yielded meaningful results, a few limitations should be acknowledged. First, the use of a cross-sectional design restricts the ability to infer causality; the model identifies associations rather than temporal cause-and-effect relationships. Second, although the pseudo-R^2 value was relatively high, pseudo-R-squared metrics in logistic regression do not have a direct interpretation equivalent to R^2 in linear regression and should be interpreted with caution. Third, several barrier variables were dichotomised, which may have resulted in the loss of nuanced responses originally captured on ordinal scales. Lastly, while multicollinearity was checked using tolerance values (all > 0.3), some moderate correlations may still exist, which could potentially influence the stability of coefficient estimates.

2.11. Ethical Considerations

This study obtained ethical clearance (Approval No. NWU-00323-18-A9) from the Research Ethics Regulatory Committee of Northwest University. All participants were informed about the purpose of the research and participated voluntarily, understanding that they could withdraw from completing the questionnaire at any point without consequences. The confidentiality of respondents' information was strictly maintained, and data were used solely for academic purposes.

3. RESULTS AND DISCUSSION

3.1. Socio-Economic Characteristics of Respondents

A total of 121 small-scale farmers participated in the survey. *Table 2* presents the socio-economic profile of these respondents. The sample was predominantly male (63%), with females making up (37%). This male majority reflects the gender distribution often observed in small-scale farming in the region, where men tend to have more access to land and farming resources, although women also play significant roles.

In terms of education, about one-third of the farmers (33%) had only primary education, 31% had reached secondary school, and 20% had no formal schooling (informal education). A smaller segment had post-secondary education: 9% had a college-level qualification, and 7%

had a university degree. This generally low level of formal education among the farmers suggests potential challenges in dealing with complex technologies and information, and it underscores the importance of delivering ICT solutions that are accessible to users with limited literacy or educational background.

Regarding marital status, just over half of the respondents (51%) were married, while about one-third (31%) were single. The remaining (16%) were divorced or separated. There were few widowed respondents recorded (if any, they were included in the "divorced/other" category). Marital status can sometimes influence farm decision-making dynamics and openness to new practices; for instance, married farmers might have larger households that could either support or constrain ICT adoption through labour availability or competing financial priorities.

The age distribution was skewed towards older farmers, with nearly half (49%) of the respondents being above 50 years old. (40%) The majority were in the 41–50 years age bracket (8%), followed by those in the 31–40 years age group (8%), and only 3% were in their twenties (21–30 years old). The predominance of older farmers (with almost 90% being over 40) is notable. Older age can be associated with lower technology adoption rates in agriculture, as younger farmers are often more open to trying new ICT tools. The ageing farming population in Mahikeng may therefore contribute to a slower uptake of ICT, as also observed in other rural communities.

Household sizes among respondents were moderate to large. Most farming households (around 60%) consisted of 4–6 members. About 23% had only 1–3 members, and roughly 17% had 7–10 members. Only a few households were very large: less than 2% had more than 10 members. The average household size falling in the 4–6 range suggests that many farmers have families or dependents who could both contribute to farm labour and benefit from farm incomes. A larger household might mean more labour available to assist with farming, but it can also mean more financial pressure, which might limit funds available for investing in ICT tools.

Farmers in the study were generally experienced. A plurality (about 40%) reported 11–20 years of farming experience, and roughly one-third (33%) had 2–10 years of experience. About 20% had 21–30 years of farming experience, and nearly 5% had 31–40 years of farming experience. A small number (approximately 2%) had over 40 years of experience in farming. This suggests that many respondents possess long-standing knowledge and farming practices, which could

Vol. 54 No. 1, 2026: 190-223
10.17159/2413-3221/2026/v54n1a20927

influence their perception of new technologies. Experienced farmers may be accustomed to traditional ways, or conversely, they may recognise how information access has evolved over the decades. The high proportion with over a decade of farming suggests that interventions to introduce ICT need to account for entrenched habits and possibly provide clear demonstrations of added value to convince older farmers.

The farm sizes operated by respondents were relatively small, as expected for small-scale farmers. Nearly half (47%) of the farmers cultivated land ranging from 0 to 2 hectares, and 39% had landholdings of 3 to 6 hectares. Only 9% had mid-sized farms of 7–10 hectares, and an even smaller fraction (about 5% combined) had farms larger than 10 hectares. These small farm sizes imply limited financial margins and capital, which can constrain the ability to purchase ICT devices or pay for services. On the other hand, smaller farms might greatly benefit from precise and timely information, for instance, to maximise output on limited land, so affordable ICT solutions could have a high impact if barriers are overcome.

Annual household income from farming was modest for most respondents. Nearly half (46.3%) reported an annual income between R10,000 and R30,000 (South African Rand), and about one-third (32.2%) earned between R31,000 and R50,000 per year. About 10% had incomes in the R51,000–R70,000 range, and 4% incomes in the R71,000–R90,000 range. Only about 7% earned more than R91,000 annually from their farming activities. This finding, that nearly half of small-scale farmers in Mahikeng earned between R10,000 and R30,000 annually, is consistent with evidence from the Eastern Cape, where smallholder farmers reported an average annual income of R26,600 (Zantsi *et al.*, 2019). These figures, though from different provinces, highlight a common trend of modest farm incomes among small-scale producers in South Africa, underlining a critical economic constraint. With such limited financial resources, it is understandable that many farmers would be hesitant or unable to invest in ICT hardware, such as smartphones or computers, or incur recurring costs like internet data plans. The affordability of technology emerges as a likely significant barrier, given this income profile.

In terms of farming enterprises, the respondents were not exclusively specialised. About 16% of the farmers engaged solely in livestock production, while the majority practised mixed farming (72%). It was observed that very few (12%) were strictly crop-only farmers; instead, many smallholders diversify to spread risk. Mixed farming can influence the types of information needed, for instance, market prices for both crops and livestock, weather for crops, and veterinary information for animals.

When asked about their primary sources of agricultural information, 36% of the farmers cited fellow farmers, i.e. peer networks, as their most significant source, and 35% relied on agricultural extension agents provided by government or NGOs. This leaves radio and other traditional media as the least-cited primary source at 29%. These percentages suggest that interpersonal communication remains crucial as farmers trust advice from peers and extension officers, while radio, although used by nearly one-third, is comparatively less dominant as the first choice. The reliance on fellow farmers and extension workers indicates that any ICT interventions might be more readily accepted if they are integrated with these existing information networks. For example, using radio programs or mobile messaging that involve extension advice or farmer discussion forums.

Awareness of ICT for accessing agricultural information was found to be very high: 92% of respondents stated that they were aware that ICT can be used to support the delivery of agricultural information. This is an encouraging finding, implying that a lack of awareness is not the primary issue, as most farmers are aware that technologies such as phones or the internet can serve agricultural purposes. The remaining (8%) who were not aware are a small minority, possibly very isolated or older farmers who have had little exposure to new communication tools.

Despite high awareness, actual usage of ICT tools for farming information was concentrated in a few traditional media. Most farmers reported using television (30.9%), radio (27.7%), and mobile phones (27.2%) as their primary ICT-based tools to access agricultural information. These three media collectively account for the dominant share of usage, suggesting that many farmers stick to relatively accessible and familiar technologies. For instance, TV and radio have long been present in rural communities, and basic mobile phones are now widely available. A much smaller share of farmers uses the internet (9%) or personal computers (4%) for agricultural information, indicating that advanced digital platforms, such as online resources, smartphone apps, or computer databases, are not yet widely adopted in this community.

Additionally, about 1–2% of respondents mentioned “other” ICT tools (such as DVDs, digital cameras, or video conferencing. The low uptake of internet and computers underscores infrastructural and skill barriers: many rural areas lack broadband access or have expensive data plans, and farmers may not have the necessary training to use computer-based tools. Moreover, smartphones, which are capable of internet use, might not be affordable for many; hence, only a small minority leverages the full capabilities of the internet for farming needs.

Overall, the socio-economic characteristics paint a picture of an older, predominantly male farming population with limited education and income, operating small farms. These factors help contextualise the subsequent findings on ICT adoption barriers. For instance, lower literacy and education levels are associated with the latter finding that digital literacy is a problem for over half of the farmers. Similarly, the low-income levels correspond with the finding that cost is a major barrier. The following section discusses these barriers in detail, linking them with both the quantitative results from the survey and comparable findings from other studies.

TABLE 2: Socio-Economic Characteristics and ICT Use Among Respondents

Socio-economic Variable	**Categories**	**Frequency**	**Percentage (%)**
Gender	Male	76	63
	Female	45	37
Level of Education	Informal	24	20
	Primary	40	33
	Secondary	38	31
	College	11	9
	University	8	7
Marital Status	Single	40	31
	Married	62	51
	Divorced	19	16
Age	21–30 years	4	3
	31–40 years	10	8
	41–50 years	48	40
	51 years and above	59	49
Household Size	1–3 members	28	23

	4–6 members	72	59.5
	7–10 members	20	16.5
	11–13 members	1	1
	14 members and above	0	0
Farming Experience	2–10 years	40	33.06
	11–20 years	28	39.67
	21–30 years	24	19.83
	31–40 years	6	4.96
	41–50 years	2	1.65
	51+ years	1	0.83
Farm Size (ha)	0–2 hectares	57	47
	3–6 hectares	47	39
	7–10 hectares	11	9
	11–15 hectares	2	2
	16 hectares and above	4	3
Annual Income (ZAR)	10,000–30,000	56	46.3
	31,000–50,000	39	32.2
	51,000–70,000	12	10
	71,000–90,000	5	4.1
	91,000 and above	9	7.4
Type of Farm Enterprise	Crop production	15	12
	Livestock production	19	16
	Both	87	72
Information Sources	Extension agents	111	35
	Fellow farmers	114	36

10.17159/2413-3221/2026/v54n1a20927

	Radio	92	29
Awareness of the Use of ICTs	Yes	111	92
	No	10	8
Use of ICTs for Information Access	Yes	104	86
	No	17	14
ICTs Used by Small-scale Farmers	Radio	105	27.7
	Television	117	30.87
	Mobile phones	103	27.18
	Internet	34	8.97
	Video conferencing	1	0.26
	Personal computer	15	3.96
	DVDs and CDs	2	0.53
	Digital cameras	2	0.53
	Telecentres	0	0

***Note**: Respondents could select more than one option for "Information Sources" and "ICTs Used by Small-scale Farmers". Percentages are based on the total number of respondents (n = 121) and may therefore exceed 100%. Additionally, currency is in South African Rand (ZAR).*

3.2. Barriers to ICT Adoption for Accessing Agricultural Information

The study identified a range of barriers that small-scale farmers face when using ICT to access agricultural information. *Table 3* summarises the surveyed barriers, showing the proportion of farmers who rated each as a “major constraint” versus a “minor or not a constraint.” The discussion below highlights the most significant barriers and provides context by comparing with findings from other studies.

3.2.1. Major Barriers

The most cited barrier was the poor infrastructure in rural areas, reported as a major constraint by 85% of the respondents. The rural environment in which these farmers operate often lacks essential technological infrastructure, such as reliable electricity, telephone lines, and broadband internet coverage, which is critical for effectively accessing and using ICT. Many farming communities in Mahikeng experience frequent power outages (Loadshedding) or have no grid connection at all, and network signal coverage can be weak or non-existent outside of town centres. This finding aligns with widespread challenges in many rural parts of South Africa and sub-Saharan Africa as a whole, where infrastructure development has lagged behind in urban areas. For instance, Makaula and Yusuf (2021) note that inadequate infrastructure, such as electricity and telecom networks, remains a primary barrier to ICT uptake in rural Eastern Cape communities. In the context of our study, without improvements in basic infrastructure, farmers have a limited ability to charge devices, maintain internet connectivity, or even receive radio/TV signals consistently. Thus, poor infrastructure undercuts nearly all other efforts to leverage ICT and must be addressed as a foundational step.

The second most prevalent barrier was the lack of ICT-related facilities such as telecentres, identified by 79% of respondents as a major challenge. Telecentres are community venues equipped with computers, internet access, and other communication services, intended to provide public access to those who cannot afford private devices or connections. In Mahikeng's rural villages, such facilities are largely absent. Their absence means that if a farmer does not personally own an ICT device or cannot afford internet data, there are few alternatives for them to access the internet or use digital services. Even those who own basic phones might benefit from telecentre services, such as printing information, accessing advanced applications, or receiving training. The importance of telecentres and similar shared facilities is echoed in another research. Mishra *et al*. (2020) found that farmers in rural India faced various constraints in ICT utilisation, including a lack of awareness, insufficient training, and the absence of infrastructure such as telecentres, internet kiosks, and a reliable power supply. Our findings support this, indicating that establishing community ICT hubs could significantly alleviate some barriers, particularly for resource-poor farmers who cannot afford to invest in expensive ICT resources individually.

Data bundle costs were highlighted as a major constraint by 73% of the farmers. South Africa is known to have relatively high mobile data costs compared to many other countries, which is particularly burdensome for low-income users in rural areas. For small-scale farmers operating on tight profit margins, spending money on internet data competes with other essential needs. A majority indicated that even if they have a phone that can access the internet, they often cannot afford to purchase enough data to regularly use services like online markets, weather apps, or agricultural extension WhatsApp groups. This finding is well-documented by other studies; for example, Fosu and Van Greunen (2021) report that in rural Eastern Cape, the expense of internet access is a significant barrier to ICT use. High data costs, combined with low household incomes, create a situation where digital connectivity is viewed as a luxury. The implication is that interventions to reduce data costs, such as subsidised data for farmers or community Wi-Fi hotspots, could make a meaningful difference in ICT adoption.

Compounding the cost issue is poor network connectivity, which was noted by about 55% of the farmers as a major problem, either standalone or related to data usage. Even when farmers purchase data, they may still struggle with slow speeds, dropped connections, or a weak network signal in their fields or homes. Such unreliable connectivity reduces the perceived value of using internet-based ICT tools. Our findings here align with those of Mehrabi *et al.* (2021), who noted that a “digital divide” in agriculture often arises from high data costs and inadequate network infrastructure, leaving small-scale farmers at a disadvantage in accessing data-driven farming technologies. Thus, improving the telecommunications network, i.e., adding more cell towers or enhancing coverage, is just as important as making data affordable; both complement each other in enabling farmers to have online access when needed.

Another 71% of respondents identified the high cost of ICT tools, such as smartphones and computers, as a major barrier. Many small-scale farmers cannot afford the upfront cost of purchasing modern ICT devices. For example, smartphones that can run agricultural apps or connect to the internet may be priced beyond what an average farmer earns in a month or even a year. Additionally, the cost of maintaining devices, including repairs, charging, and accessories, adds to the burden. This result highlights the financial limitations of farmers and reflects a broader issue of digital affordability. As Parvathy and Dolli (2019) found in India, the high cost of gadgets was a top-ranked barrier for farmers, with more than half of their respondents unable to keep up with modern agricultural technologies due to these expenses.

Our study's context is similar: without external support or cheaper device options, many farmers continue farming without digital tools, prioritising immediate farm inputs and household needs over technology purchases.

It is interesting to note that while 71% said the cost of devices is a major issue, a similar proportion (71%) also reported internet connectivity challenges as a major barrier, which includes aspects of both coverage and perhaps quality of connection. The overlap of these groups likely indicates that the same farmers suffering device poverty are also those in poorly connected areas; they face a dual hurdle of not having the right device, and even if they did, not having reliable internet. This combined barrier creates a significant digital exclusion.

A significant portion of farmers (55%) admitted that a lack of technical know-how or low digital literacy is a major challenge for them. This refers to the skills and confidence needed to operate ICT devices and navigate information platforms. Many small-scale farmers, particularly the older ones and those with limited formal education, are unfamiliar with using smartphones, computers, or even basic phone functions beyond making calls and sending SMS messages. They may have difficulty with tasks such as searching for information on the internet, using mobile apps, or interpreting the information they find. This highlights an important human capacity gap: even if infrastructure and cost barriers are overcome, farmers will not benefit from ICT unless they also possess the necessary skills to use the technology effectively. Barbier (2023) emphasises that bridging the digital divide in rural areas requires not just technology deployment but also investments in improving digital literacy among users. Our findings concur that over half of the respondents require training or assistance to use ICT tools comfortably. The implication is that programs aiming to promote ICT in agriculture should incorporate training sessions, demonstrations, and user-friendly interfaces tailored for farmers with little prior exposure to technology. Without building this capacity, ICT tools might remain underutilised even if they are available and affordable.

3.2.2. Other Noteworthy Barriers

Beyond the above major issues, the study also identified other barriers that, although less frequently cited as "major," are still noteworthy due to their impact on a substantial subset of farmers and often are interrelated with the primary barriers.

Exactly 50% of respondents indicated that language is a barrier to their use of ICT for agricultural information. Many ICT platforms, applications, and even devices operate in English, which is not the first language of most small-scale farmers in Mahikeng, who often speak Setswana. When agricultural information, such as weather updates, farming tips, and market news, is provided through ICT channels in a language that farmers are not fully comfortable with, the utility of that information decreases significantly. Even literate farmers may struggle with technical terminology if it's not in their mother tongue. This challenge was similarly observed by Matsenjwa *et al*. (2019), who noted that the complexity of ICT tools and content, often delivered in non-native languages, poses a significant hurdle for farmer engagement with these technologies. The result is that even if a farmer has a smartphone and internet access, they might not use an agricultural app if it is written in English, or they might misinterpret critical information. Addressing this requires more localised content, such as providing interfaces and information in local languages, employing audio/video content for those who cannot read English, or offering translation support through extension services.

Closely tied to language and digital skills are general education and literacy barriers, which 50% of respondents also cited as a barrier to ICT adoption. Low formal education can limit a farmer's ability to effectively use ICT in multiple ways: it may reduce their confidence in trying new technologies, make it harder to troubleshoot issues, and hinder their understanding of written information. The fact that half viewed their education level as a barrier corresponds with the earlier demographic data, which shows that a significant share had only primary schooling or less. This highlights the need for straightforward, user-friendly ICT solutions, as well as potential intermediary support. As Awan *et al*. (2019) found in rural Pakistan, low literacy levels among farmers restricted their ability to use ICT tools effectively, and they recommended targeted literacy programs and training as a remedy. In Mahikeng, adult education programs or ICT literacy workshops tailored to farmers could empower them to better utilise digital resources effectively. Moreover, designing ICT interfaces that use more visuals, symbols, or voice commands could also help bypass some literacy limitations.

In summary, the results revealed that the key barriers to ICT adoption for agricultural information access in Mahikeng are infrastructural (lack of electricity, network, facilities), economic (high costs of devices and data), and personal (low digital literacy, language and education limitations). These barriers are interlinked and often reinforce one another. For

Vol. 54 No. 1, 2026: 190-223
10.17159/2413-3221/2026/v54n1a20927

example, an older farmer with limited formal education (personal barrier) who lives in a village with an unreliable electricity supply (infrastructure barrier) and earns under R30,000 per year (economic barrier) is extremely unlikely to adopt ICT, even if they are aware of its potential benefits. The implication for policy and development interventions is that a holistic approach is needed. Efforts must be made simultaneously to improve rural infrastructure (electricity and internet coverage), make ICT access more affordable (through subsidies or low-cost options for devices and data), and build human capacity (by training farmers to use technology, providing content in local languages, and integrating extension support). Addressing only one barrier in isolation, for instance, handing out smartphones without providing network coverage and training would yield limited success.

The findings of this study align with the broader literature on digital inclusion in agriculture, y*et al*so provide localised evidence for Mahikeng. By quantifying the number of farmers affected by each barrier, we can prioritise interventions. Clearly, infrastructure and cost factors stand out, suggesting that any ICT adoption program should coordinate with government infrastructure projects and possibly establish public-private partnerships with telecom providers. Additionally, the significant role of literacy and language means extension services and NGOs must continue to act as intermediaries, translating and simplifying digital information for farmers until such time that farmers themselves are equipped to handle ICT independently.

TABLE 3: Barriers to Small-Scale Farmers' Use of ICT in Accessing Agricultural Information (n = 121)

Barrier	**Major Barrier (Frq %)**	**Minor Barrier (Frq %)**	**Not a Barrier (Frq %)**	**Mean**	**SD**
ICT tools are expensive to purchase	86 (71%)	27 (22%)	8 (7%)	2.64	0.60
Language is a barrier to using ICT	61 (50%)	37 (31%)	23 (19%)	2.31	0.77
Low educational level/illiteracy	61 (50%)	37 (31%)	23 (19%)	2.31	0.77

Lack of internet connectivity (no access)	86 (71%)	19 (16%)	16 (13%)	2.58	0.71
Poor network coverage (unstable signal)	67 (55.4%)	44 (36.4%)	10 (8.2%)	2.47	0.64
Lack of technical know-how (digital skills)	66 (55%)	28 (23%)	27 (22%)	2.32	0.81
Data bundles are expensive	88 (73%)	22 (18%)	11 (9%)	2.64	0.65
Poor rural infrastructure (electricity, etc.)	103 (85%)	14 (12%)	4 (3%)	2.82	0.46
Lack of ICT-related facilities (e.g., telecentres)	96 (79%)	20 (17%)	5 (4%)	2.75	0.52

Note: *Mean values are based on a three-point scale for each item: 3 = major barrier, 2 = minor barrier, 1 = not a barrier. Higher means indicate more severe overall constraint perception.*

3.3. Multicollinearity Test

Before interpreting the logistic regression results, it is essential to verify that the independent variables included in the model do not exhibit multicollinearity, i.e., a situation where predictor variables are highly correlated with one another. High multicollinearity can distort the regression coefficients and lead to misleading conclusions (Shrestha, 2020). In this study, a multicollinearity diagnostic was performed using the Variance Inflation Factor (VIF) and Tolerance values for each predictor. According to standard guidelines, a tolerance value below 0.1 or a VIF above 10 would indicate problematic multicollinearity (Shrestha, 2020; Senaviratna & Cooray, 2019).

Table 4 shows the VIF and Tolerance for key variables like farm size, cost of ICT tools, lack of internet connectivity, high data cost, and lack of ICT facilities (these were the variables entered into the regression model as predictors). All variables had VIF values well below 5 and

Vol. 54 No. 1, 2026: 190-223
10.17159/2413-3221/2026/v54n1a20927

Tolerance values well above 0.2, suggesting that multicollinearity is not a concern in the dataset. For example, "lack of internet connectivity" had the highest VIF (~2.55) and lowest Tolerance (~0.392) among the predictors, which is still within acceptable limits. This indicates that while some predictors are correlated (as expected, e.g., poor infrastructure might correlate with lack of facilities), the correlations are not strong enough to inflate variances unduly. We can thus proceed to examine the logistic regression outcomes with confidence that the relationships identified are not artefacts of multicollinearity.

TABLE 4: Multicollinearity Test of Variables

Variables	VIF	Tolerance	Eigenvalue
Farm size	1.43	0.6992	0.1702
ICT tools are expensive to purchase	1.60	0.6237	0.1044
Lack of internet connectivity	2.55	0.3915	0.0826
Data bundles are expensive to purchase	1.16	0.4635	0.0724
Lack of ICT-related facilities	2.41	0.4154	0.0351
Mean VIF	2.19		

3.4. Logistic Regression Results: Factors Influencing ICT Adoption

Table 5 presents the estimated coefficients (log-odds) for each predictor, along with their standard errors and significance levels. The key findings from the model are summarised below:

3.4.1. Farm Size

The coefficient for farm size was positive ($\beta \approx 0.9062$) and statistically significant at the 10% level ($p \leq 0.10$). This positive coefficient indicates that farmers with larger farm holdings were more likely to adopt ICT, holding other factors constant. In practical terms, managing more hectares is associated with increased odds of using ICT tools. One possible interpretation is that larger-scale smallholders have greater financial capacity and an incentive to invest in technology, as the potential returns (e.g., improved productivity, access to markets) are greater when spread over a larger area or output. Larger farms might generate slightly more income or might be more commercially oriented, making their operators more open to innovations like ICT. This finding is consistent with the idea that farm commercialisation and scale can drive technology adoption. If a farmer sees ICT to optimise a large operation, they may be willing to allocate resources to it. Our result aligns with observations in similar contexts, such as those made by Balgah *et al*. (2022), who noted that better-resourced farmers tend to adopt ICT to improve farm management.

3.4.2. Cost of ICT Tools

The coefficient for the variable "ICT tools is expensive to purchase" was negative ($\beta \approx -0.1326$) and significant at the 10% level ($p \leq 0.10$). This means that farmers who regarded the cost of devices as a major constraint were less likely to be ICT adopters. It confirms the straightforward expectation that high device costs deter adoption: those who cannot afford or are strained by the cost of buying phones, radios, or computers generally do not use them for agricultural purposes. This factor essentially captures a financial barrier on the personal level. The negative impact of device costs on adoption echoes findings by Nyakudya *et al*. (2024) in Zimbabwe, where limited financial resources were associated with a lower likelihood of using advanced farming technologies. The policy implication is that reducing the effective cost of devices through subsidies, financing schemes, or promoting second-hand and low-cost technologies could help increase ICT uptake among farmers.

3.4.3. Poor Internet Connectivity

"Lack of internet connectivity" (representing inadequate internet services or coverage) had a substantial negative coefficient ($\beta \approx -2.9721$) and was highly significant ($p \leq 0.01$). This suggests that farmers who face poor internet connectivity are far less likely to use ICT for information. This is intuitive: if a farmer's area has no signal or extremely unreliable connectivity, many ICT tools, especially modern ones like smartphones or internet-based services, become practically unusable; thus, those farmers remain non-adopters. The magnitude of this effect in the model is significant, indicating that connectivity is a critical prerequisite. This finding underscores the urgency of improving rural network infrastructure: as long as entire communities lack connectivity, interventions focusing on training or subsidising devices may have limited impact because the basic utility of ICT is compromised. It reinforces the argument made by Poudel and Ghadei (2024) that infrastructure deficiencies, such as poor internet connectivity, severely restrict technology usage in agriculture.

3.4.4. High Data Cost

The variable for "expensive data bundles" also showed a positive coefficient ($\beta \approx 1.3170$) that was significant at the 5% level ($p \leq 0.05$). This result might initially seem counterintuitive, since we would expect high data costs to discourage adoption. However, the positive coefficient here likely reflects how the model was coded: a higher value on this variable corresponds to perceiving data cost as a major constraint (value 1 for major constraint). A positive coefficient indicates that, controlling for other factors, individuals who use ICT (adopters) are more likely to report that data costs are a major issue. In other words, active ICT users acutely feel the pinch of data expenses (since they buy data regularly), whereas non-users might not cite it as a personal constraint simply because they are not even attempting to use data. This interpretation aligns with our descriptive finding that data cost is a widely recognised barrier; even adopters may struggle to maintain their usage due to cost. Thus, the positive coefficient does not imply that high data costs encourage adoption; instead, it highlights that current ICT users identify cost as a significant pain point. This nuance aside, the broader understanding remains that data affordability is a key barrier that needs to be addressed to both encourage non-users to start using services and prevent current users from dropping out. As Wani (2021) observed in Kashmir, even when farmers adopt ICT, the ongoing high cost of internet can limit their continued usage or the extent to which they leverage the technology.

3.4.5. Lack of ICT Facilities

The variable representing the lack of ICT facilities, such as telecentres, had a positive coefficient ($\beta \approx 2.1239$) that was significant at the 5% level ($p \leq 0.05$). Interpreting this, farmers who reported the absence of ICT support facilities as a major issue were actually more likely to be ICT adopters. This might appear contradictory at first glance, but it could mean that the more tech-progressive farmers (those who have started using ICT) are the ones who strongly notice and complain about the lack of support facilities, because they would benefit from them. Non-adopters might not yet realise what they are missing in terms of support, whereas adopters know that if telecentres or ICT training were available, it would greatly enhance their usage. So, rather than implying that lack of facilities somehow pushes farmers to adopt (which is unlikely), the positive association here indicates that current ICT users feel hindered by the absence of local ICT resource centres. This highlights a need expressed by the more ICT-engaged farmers for support infrastructure, such as community internet access points, repair workshops, or digital training centres. This aligns with the findings of Akintelu *et al*. (2021) in

Nigeria: even when farmers begin using ICT, the sustainability and expansion of their use depend on having institutional support and infrastructure in place.

In summary, the logistic regression analysis provides evidence for the factors influencing ICT adoption among small-scale farmers, affirming many of the intuitive relationships and shedding light on the relative importance of each. Larger farm sizes (a proxy for better resources) increase the likelihood of adoption, while key barriers, such as device cost and poor connectivity, significantly decrease it. The analysis also uncovered that current ICT users highlight ongoing barriers (data cost, lack of facilities) that, if resolved, could further increase ICT utilisation.

These results confirm the study's hypothesis in a nuanced way: there is a significant relationship between the socio-economic characteristics of small-scale farmers and their perceived barriers, as well as their adoption of ICT for accessing agricultural information. For instance, farm size (a socio-economic characteristic) is significantly related to adoption status. Similarly, experiencing major barriers (like high costs or poor infrastructure) is strongly related to not adopting ICT. Therefore, we reject the null hypothesis of "no significant relationship"; instead, we accept that certain socio-economic factors and barrier experiences do influence ICT adoption among the farmers.

The findings here are instructive for stakeholders aiming to promote digital tools in agriculture. To increase adoption rates, strategies should focus on mitigating the key deterrents identified, including reducing costs through subsidies or cooperative purchasing of equipment and group data plans, expanding rural network infrastructure through government and private sector telecom investments, and providing training and support facilities via extension services or public telecentres. Additionally, since farm size and possibly income influence adoption, interventions might also need to be pro-poor, ensuring that even farmers with minimal operations can find value in ICT and are supported in using it. Otherwise, we risk ICT widening the gap between larger, better-off farmers and the smaller, poorer ones, with only the former adopting and benefiting from technology.

Although this study employed a strictly quantitative design, some respondents provided informal feedback during the survey administration. While not systematically analysed, these comments offer useful context. Several farmers expressed interest in using ICT if it became more affordable, noting that they had observed younger farmers using smartphones for weather updates and market prices. Such remarks reinforce the quantitative finding that cost is a major barrier, while also suggesting a latent demand that could translate into higher adoption if supportive measures were implemented.

TABLE 5: Binary Logistic Regression of the Significant Variables

Variables	Coefficient	Std. Error	Z	P>|z	Marginal effects	Tolerance
Farm size	.9062135	0.4906695	1.85	0.065***	.0477443	0.6992
ICT tools are expensive to purchase	-.1325804	0.71667	-1.85	0.064***	-.0698506	0.6237
Lack of internet connectivity	-2.972073	1.0706	-2.78	0.006*	-.156585	0.3915
Data bundles are expensive to purchase	1.316974	0.5119009	2.57	0.010**	.0693854	0.4635
Lack of ICT related facilities	2.123933	0.8608678	2.47	0.014 **	.1119003	0.4154
Constant	-.2202614	3.715509	-1.91	0.057		
Number of observations	121					
LR $chi^2(14)$ =	64.51					
Prob > chi ^{2}=	0.0000					
Psuedo R^2 =	0.6568					
Log likelihood =	-16.852644					
Marginal effect after logit=	0.97790065					

Note: *, ** and * means1%, 5% and 10% levels of significant respectively**

4. CONCLUSION AND RECOMMENDATIONS

In conclusion, the adoption of ICT among small-scale farmers in Mahikeng is significantly constrained by a combination of infrastructural, economic, and socio-cultural barriers. While awareness of ICT's potential is relatively high, practical use remains limited due to poor connectivity, high costs, low digital literacy, and limited access to locally relevant information. These challenges are further compounded by the demographic profile of the farmers, including low levels of education and income.

To address these barriers effectively, efforts should focus on expanding rural infrastructure, enhancing the affordability and accessibility of ICT tools, and integrating digital support into existing agricultural extension services. Tailored training initiatives, local-language content, and community-based access points can further improve uptake. Encouraging youth participation in agriculture may also help drive broader digital inclusion. A coordinated, context-specific approach that aligns technology with farmers' realities is essential for unlocking the full benefits of ICT in rural agricultural development.

5. FUTURE RESEARCH DIRECTIONS

Building on the findings of this study, future research should prioritise in-depth, context-sensitive investigations into the social and cultural factors influencing ICT adoption among small-scale farmers in Mahikeng. Comparative studies across other municipalities could reveal whether these barriers are widespread or locally specific, helping tailor regional or national interventions. Researchers should also evaluate how infrastructure improvements, such as reliable internet access or solar energy, impact ICT uptake over time. Affordability remains a key concern; therefore, trials involving subsidised devices, shared resources, or community-based cost models are worth exploring. Additionally, the role of digital literacy should be further studied, particularly in terms of training methods tailored to local languages and formats suitable for low-literacy users. Engaging youth as ICT ambassadors and integrating digital tools into agricultural extension services also presents promising areas for enhancing uptake. Lastly, longitudinal and mixed-methods research can help establish causal links and track the long-term effectiveness of such interventions.

6. ACKNOWLEDGEMENT

I would like to sincerely thank the Director of the Northwest Department of Agriculture and Rural Development (NWDARD) for granting permission and facilitating access to the small-scale farmers who participated in this study. I am especially grateful to the 121 respondents who voluntarily shared their time and valuable insights, making this research possible.

REFERENCES

AKINTELU, S.O., AWOJIDE, S., AKINBOLA, A.O. & ADEGBITE, W.M., 2021. Social demographic factors and information and communication technology (ICT) adoption constrains amongst small and medium scale farmers in Nigeria. *IJICTRAME*., 10: 33-41.

AWAN, S.H., AHMED, S. & HASHIM, M.Z., 2019. Use of information and communication technology ICT in agriculture to uplift small scale farmers in rural Pakistan. *AJETM*., 4: 25-33.

AWUOR, F.M. & RAMBIM, D.A., 2022. *Adoption of ICT-in-agriculture innovations by smallholder farmers in Kenya.* Available from http://dx.doi.org/10.4236/ti.2022.133007

AYIM, C., KASSAHUN, A., TEKINERDOGAN, B. & ADDISON, C., 2020. Adoption of ICT innovations in the agriculture sector in Africa: A Systematic Literature Review. *Agric & Food Secur.,* 11(22): 1-16.

BALGAH, R.A., BWIFON, D.N. & SHILLIE, P.N., 2022. COVID-19, Armed conflict and icts adoption decisions. Insights from Cameroonian Farmers. *Adv. Soc. Sci. Res. J.*, 9: 12-32.

BARBIER, E.B., 2023. Overcoming digital poverty traps in rural Asia. *Rev. Dev. Econ*., 27: 1403-1420.

BARTLETT, J.E., KOTRLIK, J.W. & HIGGINS, C.C., 2001. Organisational research: Determining appropriate sample size in survey research. *ITL & PJ*., 19: 43-50.

CHORUMA, D.J., DIRWAI, T.L., MUTENJE, M.J., MUSTAFA, M., CHIMONYO, V.G.P., JACOBS-MATA, I. & MABHAUDHI, T., 2024. Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-Saharan Africa. *J. Agric. Food Res.,* 18: p.101286.

CRESWELL, J.W. & CRESWELL, J.D., 2018 *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed). Thousand Oaks, CA: Sage Publications.

DAVIS, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*., 13(3): 319-339.

DOMGUIA, E.N. & ASONGU, S.A., 2021. ICT and agriculture in Sub-Saharan Africa: Effects and transmission channels. *Info Develop*. http://dx.doi.org/10.1177/02666669251333759

FHARAZ, V.H., KUSNADI, N. & RACHMINA, D., 2022. Pengaruh literasi digital terhadap literasi E-marketing pada petani. *J. Agribisnis Indones*., 10(1): 169-179.

FOOD FOR MZANSI., 2024. *Icymi: Northwest govt helps farming community foster food security*. Available from https://www.foodformzansi.co.za/icymi-nw-govt-helps-farming-community-foster-food-security

FOSU, A. & VAN GREUNEN, D., 2021. The digital era and rural economy development: A Case of selected small-scale farmers in the former Transkei Homelands, Eastern Cape, South Africa. *Int. J. Community Dev. Manag. Stud.*, 5: 059-074.

FOX, L. & SIGNÉ, L., 2022. *Overcoming the barriers to technology adoption on African farms*. Brookings Institution. Available from https://www.brookings.edu/articles/overcoming-the-barriers-to-technology-adoption-on-african-farms/

HOANG, H.G. & TRAN, H.D., 2023. Smallholder farmers' perception and adoption of digital agricultural technologies: An empirical evidence from Vietnam. *Outlook Agric*., 52(4): 457-468.

KOTRLIK, J.W.K. & HIGGINS, C., 2001. Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. *ITL & PJ.*, 19(1): 43.

KREJCIE, R.V. & MORGAN, D.W., 1970. Determining sample size for research activities. *Educ. Psychol. Meas*., 30: 607-610.

MAHIKENG LOCAL MUNICIPALITY., 2024. *Integrated Development Plan 2024/25*. Available from www.mahikeng.gov.za.

MAKAULA, Z. & YUSUF, F., 2021. Information and communication technologies (ICT) towards agricultural development in rural areas: Case of smallholder farmers in Umzimvubu Local Municipality of the Eastern Cape Province in South Africa. *S. Afr. J. Agric. Ext*., 49(1): 81–90.

MATSENJWA, B., GROBBELAAR, S. & MEYER, I.A., 2019. Pro-poor value chains for small scale farming innovation: sustainability improvements through ICT. *S. Afr. J. Ind. Eng.,* 30: 156-171.

MEHRABI, Z., MCDOWELL, M.J., RICCIARDI, V., LEVERS, C., MARTINEZ, J.D., MEHRABI, N., WITTMAN, H., RAMANKUTTY, N. & JARVIS, A., 2021. The Global divide in data-driven farming. *Nature Sustain*., 4: 154-160.

MHLANGA, D. & NDHLOVU, E., 2023. Digital technology adoption in the agriculture sector: Challenges and complexities in Africa. *Hum. Behav. Emerg. Technol*., 2023(1): 6951879.

MISHRA, A., YADAV, O.P., YADAV, V. & PRATAP, S., 2020. Constraints faced by farmers and suggestions for effective utilization of ICT services in agriculture in central UP. *J. Pharm. Innov*., 9(2): 121-124.

MOHAJAN, H.K., 2021. Quantitative research: A successful investigation in natural and social sciences. *J. Econom. Dev. Env. People*., 9: 50-79

MUNICIPALITIES OF SOUTH AFRICA., 2024. *Mahikeng Local Municipality (NW383*). Available from https://municipalities.co.za/overview/121/mafikeng-local-municipality-nw383

NGULUBE, P., 2025. Leveraging information and communication technologies for sustainable agriculture and environmental protection among smallholder farmers in tropical Africa. *Discover Environ*., 3(1): 9.

NORTHWEST DEPARTMENT OF AGRICULTURE AND RURAL DEVELOPMENT (DARD)., 2024. *Annual Performance Report*. Available from https://provincialgovernment.co.za/department_annual/1529/2024-north-west-agriculture-and-rural-development-annual-report.pdf

NXUMALO, G.S. & CHAUKE, H., 2025. Challenges and opportunities in smallholder agriculture digitization in South Africa. *Front. Sustain. Food Syst.*, 9: 1583224.

NYAKUDYA, S., JAMBO, N., MADUDUDU, P. & MANYISE, T., 2024. Unlocking the potential: Challenges and factors influencing the use of ICTs by smallholder maize farmers in Zimbabwe. *Cogent Econ. Financ*., 12: 2330431.

OKI, O. & AGBEYANGI, A., 2024. *Impact and necessity of ICT adoption in agriculture: Insights from regression analysis*. Available from http://dx.doi.org/10.54364/AAIML.2024.44164

ONYENEKE, R.U., ANKRAH, D.A., ATTA-ANKOMAH, R., AGYARKO, F.F., ONYENEKE, C.J. & NEJAD, J.G., 2023. Information and communication technologies and agricultural production: New evidence from Africa. *Applied Sci*., 13(6): 3918.

PARVATHY, A. & DOLLI, S., 2019. *Constraints faced by farmers in utilization of Information and Communication Technologies (ICTs)*. Available from https://www.cabidigitallibrary.org/doi/pdf/10.5555/20219838739

PETERMAN, A., BEHRMAN, J.A. & QUISUMBING, A.R., 2014. A review of empirical evidence on gender differences in nonland agricultural inputs, technology, and services in developing countries. In A. Quisumbing, R. Meinzen-Dick, T. Raney, A. Croppenstedt, J. Behrman & A. Peterman (eds.), *Gender in Agriculture*. Dordrecht: Springer, pp. 145-186.

POUDEL, P. & GHADEI, K., 2024. Exploring the constraints faced by farmers in the use of ICT mediated extension services in Arghakhanchi District of Nepal. *Asian J. Agric. Ext. Econ. Sociol.*, 42(1): 68–74.

ROGERS, E.M., 2003. *Diffusion of Innovations*. New York: Free Press.

Vol. 54 No. 1, 2026: 190-223
10.17159/2413-3221/2026/v54n1a20927

SENAVIRATNA, N. & A COORAY, T., 2019. Diagnosing multicollinearity of logistic regression model. *Asian J. Probab. Stat*., 5: 1-9.

SETSHEDI, K.L. & MODIRWA, S., 2020. Socio-economic characteristics influencing small-scale farmers' level of knowledge on climate-smart agriculture in Mahikeng local municipality, Northwest Province, South Africa. *S. Afr. J. Agric. Ext.*, 48(2): 139-152.

SHRESTHA, N., 2020. Detecting multicollinearity in regression analysis. *Am. J. Appl. Math. Stat*., 8: 39-42.

SINGH, O.P. & ARYAL, R., 2023. Factors affecting the application of Information and Communication Technologies (ICT) in the agriculture sector of Nepal. *Int. J. Biol. Innov*., 5: 74-82.

SMIDT, H.J. & JOKONYA, O., 2022. Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa. *Inf. Technol. Dev.*, 28(3): 558-584.

WANI, Y. A., 2021. Adoption of Information and Communication Technology (ICT) by Farmers in Kashmir. *Agro. Econ*., 9(01): 61-67.

ZANTSI, S., GREYLING, J.C. & VINK, N., 2019. Towards a common understanding of 'emerging farmer' in a South African context using data from a survey of three district municipalities in the Eastern Cape Province. *S. Afr. J. Agric. Ext.*, 47(2): 81–93.