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# Determinants of Digital Technologies Use for Agricultural Information Access Among Smallholder Farmers: A Case of Handeni and Muheza Districts, Tanzania

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ABSTRACT

This study explores the determinants influencing the use of digital technologies to access agricultural information among smallholder farmers in Handeni and Muheza Districts, Tanzania. Despite the agricultural sector's significant contribution to Tanzania's economy, smallholder farmers continue to face information gaps that hinder productivity. The study employs the Diffusion of Innovations Theory and uses a cross-sectional design, collecting quantitative and qualitative data from 200 respondents through surveys and interviews. Binary logistic regression was used to identify key socio-demographic and infrastructural factors influencing digital technology use. Findings reveal that while farmers generally perceive mobile phones, radio, and social media positively for accessing agricultural information, tools like mobile apps and television are less favored due to complexity and cost. Statistically significant predictors of digital technology use include age (negative association), education level, device ownership, internet access, and electricity access (positive associations). Gender disparities also influence access, with male farmers more likely to engage digitally. The study concludes that targeted interventions especially in digital literacy, infrastructure development, and localized content are essential to bridge the digital divide in rural farming communities.



## 1. Introduction

The agricultural sector is a backbone of Tanzania's economy, contributing 26.9% of GDP, 61.1% of employment, and 24% of export earnings (URT, 2021). Despite this, smallholder farmers who constitute most producers face persistent productivity challenges due to limited access to timely and reliable agricultural information (Jha et al., 2021; Van Hecke et al., 2020). Traditional sources such as field visits, demonstration farms, and extension services remain inadequate, as they cover only a fraction of the farming population (Mtega et al., 2016).

Digital technologies (DTs) such as mobile phones, radio, social media, and mobile applications present new opportunities for bridging information gaps (Qin et al., 2022; Karunathilake et al., 2023). However, adoption of DTs by smallholder farmers remains uneven due to socio-economic, infrastructural, and

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cultural barriers. Handeni and Muheza districts, while agriculturally productive, exemplify this divide, with low uptake of digital innovations despite national policy ambitions such as the *Kilimo Kwanza* reforms and Tanzania's Vision 2025 (URT, 2013).

This study investigates the determinants influencing the use of digital technologies to access agricultural information among smallholder farmers in Handeni and Muheza. The objectives are to (i) assess perceptions toward different digital technologies, and (ii) identify socio-demographic and infrastructural factors influencing adoption.

## 2. Literature review

### 2.1. Digital Technologies and Agricultural Information

Digital platforms disseminate critical information on weather forecasts, market prices, crop management, and pest control (Javaid et al., 2023). Evidence shows that access to such information improves decision-making and productivity among smallholders (Balana et al., 2022; Magesa et al., 2020).

### 2.2. Diffusion of Innovations Theory

The study is grounded in Rogers' Diffusion of Innovations (DoI) theory (Rogers, 2003), which explains how new ideas and technologies spread through populations. Adoption depends on five attributes: relative advantage, compatibility, complexity, trialability, and observability (Achuthan et al., 2020). For digital agriculture, factors such as age, education, device ownership, and extension support influence adoption (Ayim et al., 2022; Ploll et al., 2022).

### 2.3. Research Gaps

Previous studies (Asfaw et al., 2012; Karanja et al., 2020) focus predominantly on mobile phones, neglecting newer technologies such as mobile apps, websites, and social media. Few have empirically analyzed district-level socio-cultural influences on adoption. This study addresses these gaps by examining multiple digital tools and contextual differences in two Tanzanian districts.

## 3. Methods

### 3.1. Study Area

The research was conducted in Handeni and Muheza districts, Tanga Region, Tanzania. These areas were purposively selected because they lay within the project area of *Digital Literacy and Misinformation among Smallholder Farmers in Tanzania*, implemented by Sokoine University of Agriculture (SUA) and supported by Facebook's Foundational Integrity Research initiative and their agricultural importance.

### 3.2. Research Design and Sampling

This study employed a cross-sectional research design, which helped in the factors influencing digital literacy and agricultural production among smallholder farmers in the Handeni and Muheza districts. The utilization of a cross-sectional approach enabled the collection of data from a diverse group of smallholder farmers over a specific time period (Ratanachina et al., 2022). The cross-sectional research design offered a holistic perspective on the current state of the use of digital technologies and challenges faced to enhance agricultural production in the study area.

To ensure a comprehensive and representative sample, a multistage sampling technique was applied. A multistage sampling technique involves dividing a large and diverse population into stages or levels, where each stage employs a different sampling method to create a representative sample for data collection (Rahi, 2017). On the first stage, Handeni and Muheza were purposively selected because they lay within the project area of *Digital Literacy and Misinformation among Smallholder Farmers in Tanzania*, implemented by Sokoine University of Agriculture (SUA) and supported by Facebook's Foundational Integrity Research initiative. Secondly, four wards per district were purposively selected to capture diverse socio-economic and geographic conditions, enhancing the representativeness of the study.

With support from village extension officers, 100 respondents per districts with access to digital technologies from the sampled wards were randomly selected in the third stage. This provided an unbiased, balanced dataset for analyzing determinants of digital literacy and its implications for agricultural production. On the final stage eight villages in Handeni and three in Muheza were purposively selected to capture variation in digital access and agricultural practices, strengthening the study's insight into smallholders' adoption of digital technologies.

### 3.3. Data Collection

The study employed the mixed method approach in data collection to get both qualitative and quantitative data to allow a better understanding of determinants of digital technologies use for agricultural information access among smallholder farmers. The quantitative and qualitative data were concurrently collected. Therefore, primary data were collected using a pre-structured questionnaire, key informant interviews (KIIs) and focus group discussions (FGDs). The KIIs and the FGDs were guided by a checklist and an FGD guide respectively. A total of ten (8) key informants were interviewed, four from each district (i.e. 2 Village Executive Officers and 2 Ward Executive Officers). In addition, ten (8) FGDs, each involving 8 participants, were conducted, i.e., four FGDs in each district.

### 3.4. Data Analysis

Quantitative data were analyzed with binary logistic regression, estimating the probability of DT use. The model is specified as:

log(p1−p)=β0+β1X1+β2X2+⋯+βkXk+ε(1)\log\left(\frac{p}{1-p}\right) = \beta_{0} + \beta_{1}X_{1} + \beta_{2}X_{2} + \cdots + \beta_{k}X_{k} + \varepsilon \tag{1}log(1−pp)=β0+β1X1+β2X2+⋯+βkXk+ε(1)

Where:
- $p$ = probability of using digital technologies
- $X_k$ = explanatory variables (age, sex, education, income, device ownership, internet, extension services, electricity)
- $\beta$ = coefficients
- $\varepsilon$ = error term

## 4. Results

### 4.1. Perceptions of Digital Technologies

Table 1 presents the frequency and percentage distribution of farmers' responses on their perceptions of various digital technologies for accessing agricultural information. Radio and social media emerged as the most trusted sources. Specifically, 63% of respondents strongly agreed that radio provides timely and reliable agricultural information, and 36.9% strongly agreed that social media is useful for farming updates. In contrast, 84% strongly disagreed with the statement that mobile applications are effective, citing high costs, lack of localized content, and operational complexity. Mobile phones and SMS also scored poorly, with 84.5% strongly disagreeing that they were effective sources of agricultural information. Television received mixed responses, with 37.5% agreeing on its usefulness but 23% disagreeing, a reflection of limited rural electrification and affordability challenges.

Table 1. Likert Scale Showing Perception and Awareness on Diversified Digital Technologies distribution (frequency and percentage) of responses for each statement

| Statement | Social media | | Mobile apps | | Mobile phone | | Radio | | TV | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Count | Row N% | Count | Row N% | Count | Row N% | Count | Row N% | Count | Row N% |
| Strongly Agree | 73 | 36.9 | 0 | 0 | 1 | 0.5 | 126 | 63 | 39 | 19.5 |
| Agree | 107 | 54 | 4 | 2 | 13 | 6.5 | 27 | 13.5 | 75 | 37.5 |
| Neutral | 13 | 6.6 | 17 | 8.5 | 9 | 4.5 | 7 | 3.5 | 15 | 7.5 |
| Disagree | 3 | 1.5 | 11 | 5.5 | 8 | 4 | 35 | 17.5 | 46 | 23 |
| Strongly disagree | 2 | 1 | 168 | 84 | 169 | 84.5 | 5 | 2.5 | 25 | 12.5 |

*Source: Field data (2023)*

Table 2. overall perception and awareness on diversified digital technologies

| Statement | N | Mean | Std. Deviation | Remark |
|---|---|---|---|---|
| I use social media to access agricultural information. | 200 | 1.914572864 | 2.33067786 | Positive perception |
| I use mobile apps to access agricultural information. | 200 | 4.715 | 0.704454599 | Negative perception |
| I use mobile phone calls or SMS to access agricultural information. | 200 | 4.655 | 0.877396216 | Negative perception |
| I listen to agricultural information on the radio. | 200 | 1.83 | 1.252575237 | Positive perception |
| I watch TV to get agricultural information. | 200 | 2.715 | 1.34641717 | Negative perception |

*Source: Field data (2023)*

### 4.2. Overall Perception Scores

To provide a clearer summary, mean scores and standard deviations were computed (Table 2). Radio (M = 1.83, SD = 1.25) and social media (M = 1.91, SD = 2.33) recorded mean values below 2, confirming their positive perception among farmers. By contrast, mobile applications (M = 4.72, SD = 0.70) and mobile phone calls/SMS (M = 4.65, SD = 0.87) recorded mean scores above 4, indicating negative perceptions. Television scored moderately (M = 2.71, SD = 1.35), reflecting its limited but not entirely negative role.

### 4.3. Factor Analysis of Perceptions

To explore the underlying structure of farmers' perceptions, a factor analysis was conducted (Table 3). The results reveal two broad clusters of technologies. Social media (loading = 0.063, p = 0.035), mobile phone calls/SMS (0.628, p = 0.036), and radio (0.205, p = 0.045) loaded on one factor, which may be interpreted as accessible and trusted channels. By contrast, mobile applications (0.656, p = 0.029) and television (0.360, p = 0.028) formed a second factor, representing less accessible or less trusted channels.

Table 3. Factor Analysis

| Statement | X (Coefficient) | SD(Std Error) | P-value |
|---|---|---|---|
| I use social media to access agricultural information. | 0.063 | 2.33 | 0.035 |
| I use mobile apps to access agricultural information. | 0.656 | 0.71 | 0.029 |
| I use mobile phone calls or SMS to access agricultural information. | 0.628 | 0.88 | 0.036 |
| I listen to agricultural information on the radio. | 0.205 | 1.24 | 0.045 |
| I watch TV to get agricultural information. | 0.36 | 1.35 | 0.028 |

*Source: Field data (2023)*

Table 4. Binary Logistic Regression of Factors Influencing the Use or Non-Use of digital technologies to Access Agricultural Information among Smallholder Farmers

| Parameters | B | S.E. | Wald | Df | Sig. | Exp (B) | 95%C.I.for EXP(B) | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower | Upper |
| District (0) | 0.318 | 0.366 | 0.868 | 1 | 0.385 | 1.375 | -0.400 | 1.036 |
| Age | -0.066 | 0.014 | -4.632 | 1 | 0.0*** | 0.936 | -0.094 | -0.038 |
| Income | 0.011 | 0.009 | 1.204 | 1 | 0.229 | 1.011 | -0.007 | 0.029 |
| Education level (1) | 0.544 | 0.273 | 1.996 | 1 | 0.046** | 1.723 | 0.010 | 1.079 |
| Sex (1) | -1.414 | 0.396 | -3.567 | 1 | 0.0*** | 0.243 | -2.191 | -0.637 |
| Marital status (1) | 0.527 | 0.381 | 1.382 | 1 | 0.167 | 1.694 | -0.220 | 1.273 |
| Digital devices ownership (1) | 1.063 | 0.400 | 2.655 | 1 | 0.008*** | 2.896 | 0.278 | 1.848 |
| Internet access (1) | 0.778 | 0.390 | 1.995 | 1 | 0.046** | 2.178 | 0.014 | 1.543 |
| Extension services (1) | 0.625 | 0.389 | 1.605 | 1 | 0.109 | 1.868 | -0.138 | 1.388 |
| Trainings (1) | 0.469 | 0.379 | 1.238 | 1 | 0.216 | 1.598 | -0.273 | 1.211 |
| Electricity access (1) | 1.018 | 0.418 | 2.436 | 1 | 0.015** | 2.769 | 0.199 | 1.838 |
| Constant | -0.360 | 1.319 | -0.273 | 1 | 0.785 | 0.697 | -2.946 | 2.226 |

*Source Field data (2023)*

**Notes: * is significant at 0.1, ** is significant at 0.05 and *** is significant at 0.01; Omnibus tests of model coefficients (Chi-square = 81.893; sig. = 0.000); Cox & Snell R Square = 0.322; Nagelkerke R Square= 0.517*

### 4.4. Factors Influencing the use of digital technologies in accessing agricultural information

A binary logistic regression model was applied to examine determinants of digital technology use among smallholder farmers. The model was statistically significant (Omnibus $\chi^2 = 81.893$, $p < .001$), with a Cox and Snell $R^2$ of 0.322 and Nagelkerke $R^2$ of 0.517, indicating a moderate explanatory power. Age was negatively associated with digital technology use ($B = -0.066$, $p < .001$). Older farmers were significantly less likely to adopt digital technologies compared to younger counterparts. Education level positively influenced adoption ($B = 0.544$, $p < .05$), demonstrating that higher education increases the likelihood of using digital platforms. Sex was a significant predictor ($B = -1.414$, $p < .001$), with male farmers more likely than female farmers to use digital technologies. Furthermore, digital device ownership was highly significant ($B = 1.063$, $p < .01$), showing that farmers who owned smartphones or other devices were nearly three times more likely to access agricultural information digitally. Internet access ($B = 0.778$, $p < .05$) and electricity access ($B = 1.018$, $p < .05$) were both positively associated with adoption. However, monthly income was not statistically significant ($p = .229$), although the coefficient indicated a positive direction. Extension services and training did not show significant effects, although their coefficients were positive.

### 4.5. District-Level Differences in Digital Technology Adoption

Results on table 4 below show significant differences between Handeni and Muheza districts across key demographic and infrastructural variables. Notably, sex distribution differed significantly between districts ($\chi^2 = 13.829$, $p = .001$), with a higher proportion of females in Muheza (n=34) than in Handeni (n=41). A significant difference also emerged in the age structure of respondents ($\chi^2 = 9.459$, $p = .002$), where Muheza reported a larger working-age population (n=54) compared to Handeni (n=66). Similarly, ownership of digital devices was significantly higher in Muheza (n=47) than in Handeni (n=53), a difference that reached statistical significance ($\chi^2 = 6.23$, $p = .013$). Furthermore, electricity access differed significantly between the two districts ($\chi^2 = 4.952$, $p = .026$), with 51 respondents in Muheza and 56 in Handeni reporting electricity availability. In contrast, no statistically significant differences were observed in marital status ($\chi^2 = 1.126$, $p = .289$), education level ($\chi^2 = 4.355$, $p = .113$), income level ($\chi^2 = 0$, $p = 1.000$), access to extension services ($\chi^2 = 0.152$, $p = .697$), internet access ($\chi^2 = 0.704$, $p = .401$), or training participation ($\chi^2 = 1.839$, $p = .175$). These non-significant results suggest relative homogeneity in these dimensions between Handeni and Muheza.

Table 4. Cross-Tabulation of Farmers' Use of Digital Technologies for Agricultural Information by Socio-Demographic and Enabling Factors across Muheza and Handeni Districts (n = 200)

| Variable | | Districts | | | | | | Difference | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Muheza | | Handeni | | Overall | | Chi-square | df | P-value |
| | | No | Yes | No | Yes | No | Yes | | | |
| Marital status | Not married | 16 | 29 | 16 | 28 | 32 | 57 | 1.126 | 1 | .289 |
| | Married | 19 | 36 | 12 | 44 | 31 | 80 | 1.126 | 1 | .289 |
| Sex | Female | 11 | 34 | 5 | 41 | 16 | 75 | 13.829 | 1 | .001*** |
| | Male | 24 | 31 | 23 | 31 | 47 | 62 | 13.829 | 1 | .001 |
| Age | Working age population | 27 | 54 | 16 | 66 | 43 | 120 | 9.459 | 1 | .002*** |

| Variable | | Districts | | | | | | Difference | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Muheza | | Handeni | | Overall | | Chi-square | df | P-value |
| | | No | Yes | No | Yes | No | Yes | | | |
| | Older age population | 8 | 11 | 12 | 6 | 20 | 17 | 9.459 | 1 | .002 |
| Education level | No formal education | 8 | 9 | 6 | 7 | 14 | 16 | 4.355 | 2 | .113 |
| | Primary | 16 | 37 | 12 | 40 | 28 | 77 | 4.355 | 2 | .113 |
| | Secondary+ | 11 | 19 | 10 | 25 | 21 | 44 | 4.355 | 2 | .113 |
| Income | Above average | 15 | 29 | 15 | 36 | 30 | 65 | 0 | 1 | 1.000 |
| | Below average | 20 | 36 | 13 | 36 | 33 | 72 | 0 | 1 | 1.000 |
| Digital devices ownership | No | 16 | 18 | 13 | 19 | 29 | 37 | 6.23 | 1 | .013** |
| | Yes | 19 | 47 | 15 | 53 | 34 | 100 | 6.23 | 1 | .013 |
| Internet access | No | 20 | 20 | 10 | 35 | 30 | 55 | 0.704 | 1 | .401 |
| | Yes | 15 | 45 | 18 | 37 | 33 | 82 | 0.704 | 1 | .401 |
| Extension services | No | 14 | 23 | 12 | 28 | 26 | 51 | 0.152 | 1 | .697 |
| | Yes | 21 | 42 | 16 | 44 | 37 | 86 | 0.152 | 1 | .697 |
| Trainings | No | 20 | 29 | 12 | 25 | 32 | 54 | 1.839 | 1 | .175 |
| | Yes | 15 | 36 | 16 | 47 | 31 | 83 | 1.839 | 1 | .175 |
| Electricity access | No | 13 | 14 | 11 | 16 | 24 | 30 | 4.952 | 1 | .026** |
| | Yes | 22 | 51 | 17 | 56 | 39 | 107 | 4.952 | 1 | .026 |

*Source Field data (2023)*

**Notes: The Chi-square statistic is significant at the * is significant at 0.1, ** is significant at 0.05 and *** is significant at 0.01 level*

### 4.6. Discussion

#### 4.6.1. Awareness and Perceptions of Digital Technologies

This study shows that smallholder farmers in Handeni and Muheza continue to rely heavily on radio and social media for agricultural information, while mobile applications, SMS, and television are used less frequently. Such preferences are consistent with earlier findings that farmers gravitate toward tools that are simple, low-cost, and familiar, while more complex platforms are often avoided due to cost, lack of experience, and perceived difficulty (Alhassan & Haruna, 2024). The factor analysis confirmed this divide by grouping radio, social media, and SMS as “accessible and trusted” channels, while mobile apps and television formed a cluster of “less accessible and trusted” options. These patterns emphasize that structural barriers such as affordability, digital literacy, and infrastructure rather than unwillingness, limit the adoption of advanced digital tools (Silvestri et al., 2020).

These findings mirror experiences from other African contexts. Farmers in South Africa and Zimbabwe, for instance, also preferred low-cost platforms as reliable sources of agricultural advice (Mogashane, Loki, & Mazwane, 2025; Mapfumo et al., 2022). Limited uptake of mobile applications and television in the present study reflects challenges observed in Kenya and Uganda, where language, interface complexity, and lack of offline functionality restricted use (Ogutu et al., 2021; Nalubega et al., 2024).

Thus, while awareness of advanced tools exists, the practical reality is that farmers continue to depend on low-tech solutions.

#### 4.6.2. Socio-Demographic Factors

The results also highlight how socio-demographic characteristics shape digital adoption. Age negatively influenced adoption, reflecting a generational gap in digital literacy. Older farmers tended to rely on traditional practices and were less comfortable using digital platforms, a pattern consistent with studies in Ethiopia and Nigeria (Ayalew & Girma, 2025; Anaduaka & Okoye, 2023). Education, on the other hand, strongly enhanced adoption, reinforcing the argument that human capital underpins digital engagement (Nakasone et al., 2020).

Gender disparities were evident, as male farmers were significantly more likely to adopt digital tools than female farmers. This resonates with regional evidence that patriarchal structures limit women's control over phones, finances, and other enabling resources, thereby reinforcing digital exclusion (Ngigi & Muange, 2022; Nalubega et al., 2024). Infrastructure also played a critical role: access to electricity and internet substantially increased the likelihood of adoption. Farmers with electricity were nearly three times more likely to use digital platforms, underscoring how connectivity gaps perpetuate rural digital divides. Similar barriers have been documented in Tanzania and Kenya (Misaki et al., 2020; Ogutu et al., 2021). Although income was not statistically significant, its positive direction suggests that affordability constraints remain important, echoing evidence that poorer households are the least likely to engage digitally even when services are available (Fadeyi et al., 2022).

#### 4.6.3. District-Level Differences

Beyond individual characteristics, the analysis revealed meaningful district-level differences. Farmers in Muheza had higher representation of working-age individuals and women, reflecting socio-economic vibrancy and gender-inclusive programming reported in the Tanga region (Mwaisaka et al., 2022). Conversely, Handeni showed more pronounced deficits in device ownership and electricity access, highlighting the uneven spread of technological infrastructure. These disparities align with national concerns about unequal ICT development, which undermine rural service delivery (Lwoga & Sangeda, 2020; World Bank, 2022).

Interestingly, some variables such as education, income, and access to extension or training services—did not differ significantly between districts. This could indicate progress toward uniformity in basic services, possibly due to the implementation of the National Digital Development Strategy (URT, 2021). However, the lack of observed differences may also stem from dataset limitations, particularly the inability to capture qualitative differences such as the type or quality of education and training received. Similarly, the absence of significant differences in internet access, despite wide gaps in device ownership, raises questions about affordability, digital literacy, and actual usage patterns. These subtler barriers align with prior studies that describe hidden layers of the digital divide (Nyamba & Mlozi, 2020; Hilbert, 2020).

#### 4.6.4. Policy and Practice Implications

Taken together, these findings demonstrate that advancing digital agriculture requires addressing deeper structural and social barriers rather than simply providing devices or platforms. While radio, SMS, and social media remain critical entry points for reaching smallholder farmers, their effectiveness depends on integrating them into broader digital ecosystems and ensuring that content is localized, reliable, and actionable. Without such integration, farmers may access information but fail to act on it.

Socio-demographic and infrastructural factors particularly gender, education, electricity, and internet access emerged as decisive enablers or barriers to adoption. These results underline the need for gender-sensitive interventions that deliberately target women and older farmers. Tailored capacity-building initiatives and digital literacy programs are essential for ensuring that digital agriculture contributes not only to productivity but also to social inclusion.

Finally, the district-level findings underscore the importance of context-specific strategies. Muheza, with its stronger demographic and infrastructural base, may be ready for scalable digital extension services. Handeni, by contrast, requires foundational investments in electricity and connectivity before more advanced services can be effective. Recognizing these local realities will be crucial for designing policies that foster equitable and inclusive digital transformation in rural Tanzania.

## 5. Conclusions

This study demonstrates that perceptions of digital technologies are generally positive, yet adoption remains uneven due to age, education, gender, and infrastructural barriers. While policy frameworks such as Vision 2025 aim to mainstream digital agriculture, localized and inclusive strategies are needed. The cross-sectional design limits causal inference, and the binary measurement of DT use may oversimplify diverse engagement levels. Longitudinal designs and multidimensional digital adoption indices are recommended to capture intensity and frequency of use.

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