UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 6(2), June (2026), 3395-3403
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Adoption and Limitations of Smartphone Plant Disease Identification Apps in Early Disease Detection Among Crop Farmers in Atiba Local Government Area, Oyo State, Nigeria

Olusola Olakunle Ogunjinmi[1]*, Olumide Olutayo Oyedare[2], Adenike Mary Durojaiye[3], and Olufunmilola Oludoyin Oluwadiran[4]
[1,2,3]Department of Agricultural Education, Faculty of Vocational, Innovation and Engineering Education, Emmanuel Alayande University of Education, Oyo, Oyo State.
[4]Department of Home Economics Education, Emmanuel Alayande University of Education, Oyo, Oyo State.
*Corresponding Author's E-mail: olumide.oyedare89@gmail.com

Abstract
Crop diseases pose a major threat to agricultural productivity in sub-Saharan Africa, with estimated yield losses of 20–40% annually, while traditional diagnostic services remain out of reach for many smallholder farmers. This study assessed awareness, adoption and constraints related to smartphone-based plant disease identification applications among 150 crop farmers in Atiba Local Government Area, Oyo State, Nigeria, using a descriptive survey design and multistage sampling. Data were collected through face-to-face administration of structured questionnaires and analysed using descriptive statistics and chi-square tests. The socioeconomic profile showed a predominantly middle-aged population with generally low to moderate education and digital experience, and although all respondents either owned or had access to smartphones, awareness of disease identification applications was only 47.3%. Adoption remained modest, with 25.3% regular users, 15.3% occasional users, and 52.7% never-users. Chi-square results indicated that age group, educational level, smartphone ownership and digital experience were all significantly associated with adoption status. Among users, perceived benefits include early disease detection (mean = 3.42), reduced crop loss (3.31), improved yield (3.18) and reduced chemical costs (3.05) all exceeded the decision threshold of 2.50. Major constraints were poor internet connectivity (3.48), high data costs (3.36), concerns about diagnostic accuracy (3.12), and low digital literacy (3.05). The study concludes that increasing adoption will require integrated efforts to improve rural connectivity and data affordability, strengthen farmers' digital skills and embed validated localised applications within extension systems.
Keywords: Smartphone, telecommunication, adopters, internet, traditional methods.

1. Introduction

Plant diseases remain a major threat to agricultural productivity and food security globally, with estimated yield losses of 20-40% annually in sub-Saharan Africa where smallholder farmers dominate crop production (Cassimiro et al., 2024). In Nigeria, agriculture employs about 70% of the rural workforce and contributes over 22% to national GDP, yet diseases affecting staple crops such as maize, cassava and yam continue to reduce yields, depress farm incomes and aggravate food insecurity (Akpa, 2024). Conventional diagnostic practices, including visual inspection by farmers, consultation with extension agents and laboratory-based testing, are largely inaccessible to many smallholders because of the shortage of extension personnel, high transaction costs and delays in obtaining laboratory results (Samson and Taiye, 2020). Early and accurate disease detection is therefore critical, as timely interventions can substantially reduce yield losses and minimise unnecessary pesticide use (Cassimiro et al., 2024).

Recent advances in artificial intelligence and mobile computing have enabled smartphone-based plant disease identification systems that use deep convolutional neural networks to analyse images captured directly in the field (Mohanty et al., 2016). These tools have achieved high diagnostic performance in experimental and field settings, often reporting accuracy levels above 90% for several crop-disease combinations, while requiring only a camera-enabled smartphone and basic mobile connectivity (Panashe, 2025; Isinkaye and Erute, 2022). Given the rapid diffusion of mobile technologies and digital agricultural services among smallholder farmers in sub-Saharan Africa, such innovations are increasingly recognised as a promising complement to conventional extension systems (Ogbeide and Ele, 2015).

At the same time, empirical research on digital agriculture indicates that the mere availability of mobile-based tools does not guarantee widespread or sustained adoption among farmers. Studies on mobile agricultural advisory and extension applications in Nigeria and other African countries highlight heterogeneous adoption patterns and show that perceived usefulness, ease of use, digital skills, local relevance of content and trust in the technology all play important roles in shaping uptake and continued use (Abioye et al., 2025). Barriers such as limited awareness, affordability constraints, language and literacy issues, and patchy network coverage continue to restrict the effective integration of mobile tools into smallholder production systems (Ik-Ugwoezuonu and Ezike, 2024). However, the existing literature has focused predominantly on general mobile advisory services, market information platforms and weather services, with relatively fewer studies examining farmer adoption of specialised smartphone-based plant disease identification applications in major rural areas.

This study addresses this gap by investigating smallholder farmers' awareness, adoption patterns, perceived benefits and constraints related to the use of smartphone-based plant disease identification applications in Oyo State, Nigeria. Specifically, the study aims to:

(i) establish baseline information on farmers' awareness, adoption and usage patterns of plant disease diagnosis applications;
(ii) (ii) identify the perceived agronomic and economic benefits associated with their use; and
(iii) (iii) document and prioritise the constraints that hinder wider and more effective utilisation among crop farmers in the study area.

This study therefore examines smallholder farmers in Oyo State and adds to existing work on digital agriculture and technology adoption among African smallholders. It also provides practical guidance for extension services and technology developers on how to design and scale inclusive digital plant health solutions in Nigeria (Abioye et al., 2025).

2.0 Materials and methods

2.1 Study Area

The study was conducted in Atiba Local Government Area, situated within Oyo State in southwestern Nigeria. Atiba LGA represents a predominantly agrarian region where agricultural activities concentrate on crop production systems encompassing maize (*Zea mays*), cassava (*Manihot esculenta*), yam (*Dioscorea* spp.), and diverse vegetable crops cultivated primarily through smallholder farming operations averaging between 0.5 and 8 hectares per household. The area experiences a tropical savanna climate characterised by distinct wet and dry seasons, with rainfall patterns supporting rainfed agriculture as the dominant production system and occasional supplementation through small-scale irrigation in valley bottom areas. Settlement patterns across Digital infrastructure development in the locality represents an intermediate state, with mobile telephone network coverage provided by multiple telecommunications operators including MTN, Airtel and Glo, while internet accessibility remains constrained with inconsistent coverage quality and frequent service interruptions. Electricity supply follows an intermittent pattern, with grid-connected communities experiencing regular power outages and numerous settlements relying entirely on alternative energy sources including generators, solar panels, and battery systems.

2.2 Method of Data Collection

A multistage sampling procedure was employed to select respondents for this descriptive cross-sectional survey. In the first stage, six farming communities within Atiba Local Government Area were selected by simple random sampling from the official list of agricultural communities obtained from the Oyo State Agricultural Development Programme, in order to capture variation in production conditions and ensure that each eligible community had an equal chance of inclusion. The choice of six communities is justified by logistical constraints and the need to achieve adequate coverage across the LGA, while still allowing for sufficient observations within the study area.

In the second stage, community-level enumeration exercises were conducted, in collaboration with farmers' associations and community leaders, to compile updated lists of crop farmers who were actively engaged in production and who owned a smartphone or had regular access to one within the household or through sharing arrangements.

These lists served as the sampling frames for each community. In the third stage, twenty-five eligible crop farmers were selected from each community using systematic random sampling from the community lists, yielding a total sample size of 150 farmers. The fixed allocation of twenty-five respondents per community was adopted to balance statistical precision with feasibility and to ensure that no single community dominated the sample, thereby enhancing comparability across communities and supporting a reasonable level of representativeness of smartphone-using crop farmers in the LGA.

Data were collected through face-to-face administration of a structured questionnaire that was specifically designed for this study and pre-tested in a comparable rural community outside the sampled sites to refine question wording and response options. The instrument comprised closed-ended questions, Likert-scale items on attitudes and perceptions, and a small number of open-ended questions that allowed respondents to describe their experiences in their own words. Data collection took place during the early agricultural season (April to July), when farmers were actively engaged in crop management and disease monitoring, which increased the likelihood that responses reflected current practices and heightened receptivity to technology-related inquiries.

2.3 Method of Data Analysis

Collected data were systematically coded, entered into IBM Statistical Package for Social Sciences (SPSS) software version 25.0. Analytical procedures encompassed descriptive statistical technique appropriate to the research objective. Descriptive analysis included frequency distributions, percentage calculations, and computation of measures of central tendency (arithmetic means) and dispersion (standard deviations) for all variables.

3.0 Result and Discussion

3.1 Socioeconomic Characteristics of Respondents

Table 1: Distribution of Respondents by Age

Age Range (Years)	Frequency	Percentage (%)
Below 30	22	14.7
31–40	41	27.3
41–50	53	35.3
Above 50	34	22.7
Total	150	100.0

Source, Field Survey, 2025

The socioeconomic profile of study respondents reveals a farming population characterised by middle-aged adults, moderate educational attainment, and established agricultural experience, factors with significant implications for technology adoption capacity and digital literacy development. The age distribution demonstrates that respondents comprised predominantly mature farmers, with 35.3% falling within the 41–50 age bracket and 22.7% exceeding 50 years (Table 1). This relatively mature demographic profile reflects the broader pattern documented across Nigerian smallholder agriculture wherein farming populations are aging as younger individuals increasingly migrate to urban areas seeking non-agricultural employment opportunities (Ugbohme et al., 2025). The age structure carries important implications for technology adoption, as empirical research consistently demonstrates inverse relationships between farmer age and digital technology uptake, with older farmers exhibiting lower digital literacy levels, greater resistance to technological change, and reduced capacity to navigate complex digital interfaces compared with younger cohorts (Adelakun and Olupitan, 2022).

Table 2: Distribution of Respondents by Educational Level

Educational Level	Frequency	Percentage (%)
No Formal Education	28	18.7
Primary Education	47	31.3
Secondary Education	51	34.0
Tertiary Education	24	16.0
Total	150	100.0

Source, Field Survey, 2025

Educational attainment exhibited considerable heterogeneity across the respondent population, with 34.0% possessing secondary education as their highest formal qualification, 31.3% having completed only primary education, 18.7% reporting no formal educational credentials, and merely 16.0% having attained tertiary-level qualifications (Table 2). This distribution indicates that approximately half the farming population (50.0%) possesses limited formal educational background not exceeding primary school completion, a pattern that potentially constrains capacity to engage effectively with text-based digital interfaces, comprehend technical agricultural terminology, evaluate online information credibility, and troubleshoot technical difficulties encountered during application usage (Adelakun and Olupitan, 2022). Educational level represents a consistently significant predictor of technology adoption in agricultural contexts, as formal education enhances cognitive flexibility, facilitates acquisition of digital skills, strengthens capacity to process complex information, and increases confidence in engaging with novel technologies (Ogunjobi, 2024).

Table 3: Smartphone Ownership and Digital Experience of Respondents

Variable	Frequency	Percentage (%)
SMARTPHONE OWNERSHIP STATUS		
Own smartphone	112	74.70
Access via household/peer	38	25.30
YEARS OF SMARTPHONE USE (OWNERS ONLY)		
≤ 3 years	39	34.80
4–6 years	46	41.10
≥ 7 years	27	24.10
SELF-RATED DIGITAL EXPERIENCE		
Low	52	34.70
Moderate	69	46.00
High	29	19.30

Source: Field survey, 2025

All respondents either owned a smartphone (74.70%) or reported reliable access through household members or sharing arrangements (25.30%), confirming that device access itself is not the primary barrier to adoption in this sample. Similar to findings from studies on mobile technology among African farmers, many respondents had several years of smartphone use but still reported low or moderate digital experience, indicating that routine phone ownership does not automatically translate into advanced application use (Adelakun and Olupitan, 2022). The fact that minority of farmers rated their digital experience as high is consistent with evidence that constrained digital literacy and proficiency limit the intensity and sophistication of digital agriculture adoption, even where devices are available (Musungwini et al., 2024; Nxumalo and Chauke, 2025).

3.2 Awareness and Adoption of Smartphone Plant Disease Identification Applications

Table 4: Awareness of Smartphone Disease Identification Applications

Awareness Status	Frequency	Percentage (%)
Aware	71	47.3
Not Aware	79	52.7
Total	150	100.0

Source, Field Survey, 2025

Awareness of smartphone-based plant disease identification applications among the study population reached moderate levels, with 47.3% of respondents reporting knowledge of the existence of such technological tools while 52.7% indicated complete unawareness of disease identification applications accessible through mobile devices (Table 3). This pattern of partial awareness suggests that while information regarding emerging agricultural technologies is gradually diffusing through rural areas, dissemination processes remain incomplete, with substantial proportions of the farming population yet to receive exposure to information about available digital disease diagnostic options.

The moderate awareness level documented in this investigation can be attributed to multiple interconnected factors limiting information flow in rural areas such as acute shortage of agricultural extension personnel, with current extension worker-to-farmer ratios estimated at 1:3,000 substantially exceeding the internationally recommended standard of 1:500, thereby constraining capacity for systematic technology information dissemination (Samson and Taiye, 2020; Ik-Ugwoezuonu and Ezike, 2024); limited reach of digital extension information channels including agricultural websites, mobile applications, and social media platforms within the study area, reflecting broader infrastructure and connectivity constraints; and the characteristics of farmer social networks and information exchange patterns that preferentially transmit information about familiar crop protection methods and traditional agricultural practices rather than emerging digital innovations requiring smartphone access and digital competencies (Smidt and Jokonya, 2022; Ugbohme et al., 2025).

Table 5: Level of Adoption of Smartphone Disease Identification Applications

Adoption Level	Frequency	Percentage (%)
Regular Users	38	25.3
Occasional Users	23	15.3
Tried Once	10	6.7
Never Used	79	52.7
Total	150	100.0

Source, Field Survey, 2025

Regular users, defined as farmers who used disease identification applications at least weekly during the growing season, accounted for 25.3% of respondents, while 15.3% were occasional users and 6.7% had tried the applications only once (Table 5). The fact that more than half of the respondents (52.7%) had never used such applications despite having access to smartphones confirms that device availability alone is insufficient to guarantee adoption. This echoes findings from studies on mobile agricultural services which report high phone ownership but comparatively low use of specialised m-services (Adelakun and Olupitan, 2022; Cassimiro et al., 2024). The adoption pattern documented in this study aligns closely with Rogers' (2003) Diffusion of Innovations theoretical framework, which conceptualises technology adoption as a progressive process occurring through sequential stages across distinct adopter categories ranging from innovators and early adopters through early majority, late majority, and laggards. Within this theoretical framework, the current respondent population appears to comprise predominantly members of the early adopter and early majority categories, with regular and occasional users (collectively 40.6%) representing active technology embracers while the substantial non-adopter (52.7%) represents potential late majority and laggard populations requiring more intensive persuasion efforts, demonstration of observable benefits, and provision of supportive infrastructure and technical assistance to facilitate adoption.

Table 6: Determinants of Adoption of Smartphone Disease Identification Applications

Variable	χ^2	df	p-value	Decision
Age group	22.61	3	<0.001	Significant
Educational level	12.60	3	0.0056	Significant
Smartphone ownership	18.65	1	<0.001	Significant
Digital experience	26.92	2	<0.001	Significant

Source: Field Survey, 2025

The Chi-square analysis revealed statistically significant relationships between farmers' socio-demographic characteristics and the adoption of smartphone disease identification applications (Table 6). The results showed that age group was significantly associated with adoption ($\chi^2 = 22.61$, df = 3, $p < 0.001$), with younger farmers (below 30 years and 31-40 years) recording relatively higher numbers of users compared with non-users, while farmers above 50 years had substantially more non-users. Similarly, educational level showed a significant association with adoption ($\chi^2 = 12.60$, df = 3, $p = 0.0056$). Farmers with secondary and tertiary education recorded higher adoption rates, whereas those with no formal education or only primary education were more represented among non-users. These patterns indicate that both age and education influence the likelihood that farmers will adopt smartphone-based technologies for disease identification. The results further showed that technological access and digital competence significantly influenced adoption behaviour ($\chi^2 = 18.65$, df = 1, $p < 0.001$), indicating that farmers who personally owned smartphones were much more likely to use disease identification applications compared with those relying on shared access through family members or peers. In addition, digital experience had the strongest association with adoption ($\chi^2 = 26.92$, df = 2, $p < 0.001$). Farmers who reported high digital experience recorded the highest number of users, while those with low digital experience had a substantially higher number of non-users, suggesting that digital literacy and familiarity with mobile technologies play important roles in the effective utilisation of smartphone-based agricultural tools.

These findings are consistent with previous studies on digital agriculture adoption. Akinyemi et al., (2024) has shown that younger farmers are generally more receptive to digital agricultural innovations because they are more familiar with smartphones and modern technologies, while older farmers are less likely to adopt such tools due to lower digital literacy and technological confidence. Kolapo and Didunyemi (2024) also indicated that education significantly increases farmers' likelihood of adopting smartphone agricultural applications because educated farmers are more exposed to technological innovations and information sources. Furthermore, research on digital tools in agriculture highlights that limited digital skills, inadequate access to devices, and lack of training remain major barriers to the adoption of digital agricultural technologies among rural farmers. Consequently, improving farmers' access to smartphones, strengthening digital literacy, and providing targeted training programs may significantly enhance the adoption of smartphone-based disease identification applications and other digital agricultural innovations.

3.4 Benefits of Early Disease Detection Using Smartphone Applications

Table 7: Perceived Benefits of Using Smartphone Applications for Plant Disease Identification

Perceived Benefit	**Mean Score ± SD**	**Rank**
Early disease detection	3.42 ± 0.87	1st
Reduction in crop loss	3.31 ± 0.91	2nd
Improved yield	3.18 ± 0.96	3rd
Reduced cost of chemicals	3.05 ± 1.03	4th
Decision Mean Threshold	**2.50**	

Source, Field Survey, 2025

Respondents reported positive perceptions of the benefits of using smartphone applications for early disease detection, with all mean scores above the decision threshold of 2.50 (Table 7). Early disease detection ranked highest (mean = 3.42), followed by reduced crop loss (3.31), improved yield (3.18) and reduced chemical costs (3.05), indicating that farmers clearly linked these tools to productivity gains and more efficient input use, similar to findings from studies on digital advisory and diagnostic services in smallholder systems. These results align with previous studies on digital agriculture, which shows that adopters commonly perceive benefits in terms of yield improvement, risk reduction and cost savings when digital tools are effectively integrated into crop management (Nxumalo and Chauke, 2025; Ding et al., 2022).

3.5 Limitations to the Use of Smartphone Disease Identification Applications

Table 8: Constraints to Adoption of Smartphone Disease Identification Applications

Constraint	**Mean Score ± SD**	**Rank**	**Severity Assessment**
Poor internet connectivity	3.48 ± 0.89	1st	Severe
High cost of data	3.36 ± 0.92	2nd	Severe
Inaccurate diagnosis	3.12 ± 1.01	3rd	Substantial
Low digital literacy	3.05 ± 0.97	4th	Substantial
Language barriers	2.89 ± 1.04	5th	Moderate
Decision Mean Threshold	**2.50**		

Source, Field Survey, 2025

Constraints to adoption in this study were mainly infrastructural and economic, as shown by the high mean scores for poor internet connectivity (3.48) and high data costs (3.36), which aligns with Choruma et al. (2024) and Nxumalo and Chauke (2025) who also identify weak rural connectivity and data affordability as central obstacles to digital agriculture uptake among smallholders in sub-Saharan Africa. Technical concerns about diagnostic accuracy (mean = 3.12) and low digital literacy (mean = 3.05) were likewise substantial, reflecting similar patterns reported by Choruma et al. (2024) and Fadeyi et al. (2022), who show that farmers' trust in algorithmic recommendations and their skills in using digital tools are key determinants of sustained technology use. Language barriers (mean = 2.89) were rated as a moderate constraint, but this still supports the argument in Choruma et al. (2024) and Nxumalo and Chauke (2025) that local language interfaces are important for improving accessibility for farmers with limited proficiency in dominant languages.

4.0. Conclusion

This study concludes that smartphone-based plant disease identification applications have substantial potential to enhance disease management and productivity among smallholder farmers in Atiba Local Government Area, Oyo State, but current adoption remains modest and uneven. Awareness is only moderate and chi-square analysis shows that adoption is significantly associated with farmer characteristics such as education level, smartphone ownership, and digital experience, indicating that socio-demographic and digital capacity factors shape who benefits from these tools. Even so, more than half of respondents with smartphone access have never used such applications, underscoring a marked gap between technical availability and effective utilisation. Among users, perceptions of benefits are consistently positive, with high mean scores for early disease detection, reduced crop loss, improved yield, and reduced chemical costs, confirming that perceived usefulness is not the main barrier to uptake. Instead, the principal constraints are infrastructural, economic, technical, and capacity related: poor internet connectivity, high data costs, concerns about diagnostic accuracy, low digital literacy, and language limitations collectively restrict widespread and sustained use. The findings indicate that increasing adoption of digital plant disease diagnostics will require coordinated strategies that simultaneously improve rural connectivity and affordability, strengthen farmers' digital skills, localise and validate application content, and embed these tools within supportive extension and institutional frameworks, rather than focusing solely on expanding the supply of technologies.

5.0 Recommendation

Based on the findings of this study, it is however recommended that:

i. Government and telecommunications providers should expand reliable rural mobile broadband coverage and implement targeted agricultural data subsidy schemes to reduce connectivity and cost barriers.
ii. Agricultural extension systems should deliver structured, practical digital literacy training programmes tailored to smallholder farmers, with specific focus on older farmers and women.
iii. Research institutions and agritech developers should localise disease identification applications by incorporating Nigerian agro-ecological conditions, locally prevalent diseases, and major indigenous languages.
iv. Smartphone disease identification tools should be formally integrated into agricultural extension services to complement traditional advisory systems and support farmer decision-making.
v. Regulatory agencies should establish quality assurance, certification, and field validation frameworks for disease identification applications to improve diagnostic reliability and farmer trust.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used perplexity AI in order to reformat the references. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Adelakun, O.E. & Olupitan, O. 2022. Level of digital literacy among crop farmers in Oyo State. International Journal of Agricultural Economics and Rural Development (IJAERD), 12(1): 16–23.

Abioye, D.O., Fadare, D.A., Omitoyin, S., Ogunniyi, A.I., Olinya, P., Shaibu, A., Nwilene, F. & Akande, A. 2025. Adoption impact and heterogeneity of mobile agricultural advisory technologies among smallholder farmers in Nigeria. Discover Agriculture, 3(1): 251.

Akinyemi, A.O., Ibitunde, I.O., Adediran, A. & Akerele, D. 2024. Awareness and perception on the use of smartphone applications for crop protection among undergraduate students in Southwestern Nigeria. Discover Agriculture, 2(1): 79.

Akpa, A.D. 2024. Food security strategy in Nigeria: Is there need for a shift in paradigm? Central Bank of Nigeria Economic and Financial Review, 59(4): 91–106.

Cassimiro, A.J.D.P.N., da Silva Ramos, E., Cabrera, V.E. & de Andrade Freitas, E.N. 2024. Milk weighing scale based on machine learning. Smart Agricultural Technology, 7: 100417.

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. Journal of Agriculture and Food Research, 18: 101286.

Ding, J., Jia, X., Zhang, W. & Klerkx, L. 2022. The effects of combined digital and human advisory services on reducing nitrogen fertilizer use: Lessons from China's national research programs on low carbon agriculture. International Journal of Agricultural Sustainability, 20(6): 1136–1149.

Fadeyi, O.A., Ariyawardana, A. & Aziz, A.A. 2022. Factors influencing technology adoption among smallholder farmers: A systematic review in Africa. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS), 123(1): 13–30.

Ik-Ugwoezuonu, L. & Ezike, C.C. 2024. Assessing the effectiveness of mobile apps in enhancing agricultural extension services delivery in Nigeria. African Journal of Sustainable Agricultural Development, 5(2): 13–31.

Isinkaye, F.O. & Erute, E.D. 2022. A smartphone-based plant disease detection and treatment recommendation system using machine learning techniques. Trees, 10(1): 1–18.

Kolapo, A. & Didunyemi, A.J. 2024. Effects of exposure on adoption of agricultural smartphone apps among smallholder farmers in Southwest, Nigeria: Implications on farm-level efficiency. Agriculture and Food Security, 13(1): 31.

Ma, W., Owusu-Sekyere, E., Zheng, H. & Owusu, V. 2025. Factors influencing smartphone usage of rural farmers: Empirical analysis of five selected provinces in China. Information Development, 41(1): 61–74.

Mhembere, P.B. 2025. Low-cost smartphone-based plant disease diagnosis for Zimbabwean farmers using transfer learning and crowdsourced image data. International Journal of Computer Applications, 187(32): 56–64.

Mohanty, S.P., Hughes, D.P. & Salathé, M. 2016. Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7: 1419.

Mrisho, L.M., Mbilinyi, N.A., Ndalahwa, M., Mrisho, A.M., Kehs, A.K., McCloskey, P.C., Murithi, H., Hughes, D.P. & Legg, J.P. 2020. Accuracy of a smartphone-based object detection model, PlantVillage Nuru, in identifying the foliar symptoms of the viral diseases of cassava CMD and CBSD. Frontiers in Plant Science, 11: 590889.

Musungwini, S., van Zyl, I. & Kroeze, J. 2024. Exploring adoption dynamics: Mobile technology in agricultural information dissemination among smallholder farmers in Gokwe South District, Zimbabwe. South African Computer Journal, 36(2): 124–158.

Nxumalo, G.S. & Chauke, H. 2025. Challenges and opportunities in smallholder agriculture digitization in South Africa. Frontiers in Sustainable Food Systems, 9: 1583224.

Ogunjobi, V.O. 2024. Determinants of adoption of USAID Markets II Project's agricultural technology by smallholder farmers in Southwest, Nigeria. Greener Journal of Agricultural Sciences, 14(1): 18–28.

Ogbeide, O.A. & Ele, I. 2015. Smallholder farmers and mobile phone technology in Sub-Sahara agriculture. Mayfair Journal of Information and Technology Management in Agriculture, 1(1): 1–19.

Rogers, E.M. 2003. Diffusion of innovations (5th ed.). Free Press.

Samson, O.S. & Taiye, O.F. 2020. Effectiveness of traditional extension models among rural dwellers in sub-Saharan African communities. International Journal, 8(4): 401–415.

Smidt, H.J. & Jokonya, O. 2022. Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa. Information Technology for Development, 28(3): 558–584.

Ugbohme, M., Agbamu, O.B. & Lasisi, A.J. 2025. Digital media and promotion of sustainable agricultural practices: A study of Nigerian farmers. International Journal of Multidisciplinary Science and Urban Management, 9(2): 119–135.