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EXPLORING ADOPTION DYNAMICS OF DIGITAL AGRI-EXTENSION SERVICES AMONG FARMERS IN PUNJAB, PAKISTAN

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ABSTRACT

This study investigates the determinants influencing the adoption of digital agri-extension services (DAES) among farmers in Punjab, Pakistan. DAES play a vital role in bridging the information gap between agricultural research and farming practices through mobile applications, SMS, social media, and online platforms. A total of 385 farmers were surveyed using a structured questionnaire, and data were analyzed using descriptive statistics, Chi-square tests, and binary logistic regression. Results revealed a relatively high awareness level (68.2%), but a lower adoption rate (47.98%), indicating a significant gap between knowledge and practical usage. Mobile phone-based advisory services had the highest adoption rate (68.8%), while online weather and market services ranked lowest (36.1%). Regression analysis identified education level (OR = 1.171, $p < 0.001$), smartphone availability (OR = 1.518, $p = 0.001$), internet quality (OR = 1.485, $p = 0.001$), and perceived usefulness (OR = 1.571, $p < 0.001$) as the most significant predictors of adoption. Institutional factors such as access to extension services (OR = 2.080, $p = 0.005$) and participation in farmer groups (OR = 1.506, $p = 0.038$) also positively influenced adoption. The study highlights the need for improved rural digital infrastructure, farmer training, and financial incentives to bridge the awareness-adoption gap and foster sustainable agricultural development.

***Keywords*:** Digital agri-extension services, Awareness, Technology adoption, Rural development.

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1. INTRODUCTION

The role of agricultural extension services is critical for enhancing the productivity and sustainability of agriculture. It impacts the life of rural dwellers by bridging the gap between scientific knowledge and farm operations (Streletskaya et al., 2023). In the past, such services were provided traditionally i.e. field/farm visits for having physical contacts in order to share knowledge. However, in the contemporary world, tthe development in information and communication technology (ICT) has transformed the information provision mechanism of extension. The idea of digital agricultural extension services (DAES) has emerged as a resourceful and novel means of delivering farmers with pertinent and timely data in the agricultural domain (Ullah et al., 2020). The services are based on mobile applications, SMS, social media, and web-based applications that provide farmers with weather forecasts, pest and disease management, market prices, and agronomic practices. It has been observed that DAES has significantly contributed to the revolution of agricultural systems, particularly in developing nations where access to real-time information is scarce among farmers (Ayim et al., 2022).

Agriculture is estimated to contribute approximately 19 percent of the national GDP and nearly 38 percent of labor force in Pakistan. Making it the backbone of the economy (Government of Pakistan, 2024). Punjab province is the main agricultural hub, known as the food basket of Pakistan, serving as a cornerstone of national food security and economic stability (GoP, 2024). However, Punjab agriculture has been experiencing several chronic issues that limit its productivity. Major challenges are depleting natural resources, climate change with unreliable weather patterns, increased pest attacks and post-harvesting losses. The issues become even more severe due to inadequate extension services (Ullah et al., 2022). The current extension systems in Punjab is constrained by insufficient resources, lack of specialized workers and high cost to cover large areas (Ali et al., 2021; Wuepper et al., 2021). Digital agri-extension is a potential solution in this respect, as it erases geographical barriers and brings agricultural innovations to farmers within a relatively brief time frame.

Introduction and success of DAES, however, a is largely depends upon the nature of rural population (i.e. their socio-economic attributes) and institutional factors. Previous studies have indicated that the most critical factors in determining whether farmers will use digital tools are education level, access to smartphones and the internet, farm size, digital literacy, and trust in information sources (Ali, 2021; Birner et al., 2021). Besides, the usefulness,

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reliability, and usability of digital services among farmers are significant factors that may impact adoption levels (Coggins et al., 2022; Amoussouhoui et al., 2022). Further, Punjab has poor infrastructure in rural aeas leading to the limited limited access to technologies, which makes the diffusion of DAES slow, particularly among smallholder farmers (Ullah et al., 2020). Understanding about the determinants associated with the success of DAES is critical, as it can enable policymakers and development practitioners to design appropriate strategies to make digital platforms more accessible and usable by rural populations.

Despite the growing presence of digital extension services, there are no empirical studies in Punjab that examine the factors behind their adoption and non-adoption. This study aims to close this gap by identifying and analyzing the drivers or detractors in the adoption of the use of DAES by farmers in the region. The specific objectives of the research include: (i) to identify the awareness and adoption levels of digital agri-extension services among the farmers (ii) to analyze the socio-economic, institutional, and technological conditions that influence the adoption and (iii) to provide recommendations making DAES more efficient

2. MATERIALS AND METHODS

The study has been conducted in the Pakistani province of Punjab. Punjab was selected due to its diversified crop systems, agricultural intensity, and relatively higher uptake of digital technologies. A multistage random sampling method was employed to select the sample. First, three districts namely Vehari, Faisalabad, and Sahiwal were selected randomly. In the second stage, two tehsils were selected randomly in each district. Next, four villages were selected randomly in each tehsils so total villages were 24. Finally, 16 farmers had been selected randomly out of these selected villages, except one village from which 17 farmers were selected, to reach a sample size of 385. This sample size was calculated using the Cochran formula (1977),

$$n_0 = \frac{Z^2 . p . q}{e^2}$$

Where:

- n_0 = required sample size
- Z = Z-value at 95% confidence level (1.96)
- p = estimated proportion of population (0.5, assuming maximum variability)
- q=1−p
- e = margin of error (0.05)

$n_0 = \frac{(1.96)^2 . (0.5) . (0.5)}{(0.05)^2} = 384.16$Data were collected through the structured questionnaire, consisting of four sections. The first was socio-economic characteristics, including age, education, farm size, Income, and farming experience. The second part was about awareness of DAES, measured using indicators that included knowledge of digital platforms. The third part was a measure of adoption of DAES on the five-point Likert scale of 1 (Strongly Disagree) to 5 (Strongly Agree). The final section included the assessment of institutional and technological variables (digital literacy, smartphone and internet access, trust in online sources of information, and training participation).

A pilot test was conducted on 20 farmers before the actual survey to determine the clarity, reliability and validity of the instrument. Modifications were made based on the feedback received in the pilot stage. The trained enumerators used face-to-face interviews and spoke the local language to overcome literacy barriers and minimize response errors.

Data was analyzed with the help of the Statistical Package of the Social Sciences (SPSS) by means of descriptive and inferential statistics. The Demographic data and the awareness were summarized through descriptive statistics such as frequencies, means, percentages, and standard deviations to summarize the demographic data and awareness level. Chi-square tests to establish relationships between categorical variables such as education level and awareness status. Finally, a binary logistic regression was performed to identify the significant predictors of the adoption of DAES. The model is expressed as:

$$\ln\left(\frac{P}{1-P}\right) = \beta0 + \beta1X1 + \beta2X2 + \ldots + \beta kXk + \varepsilon$$

Where:

- P = probability of adoption (1 = adopter, 0 = non-adopter)
- β0 = constant term
- β1,β2,…,βk = regression coefficients of independent variables
- X1,X2,…,Xk = socio-economic, institutional, and technological factors

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- ε = error term

The odds ratio (OR) was used to interpret the effect of each independent variable on the likelihood of DAES adoption. A value of OR greater than 1 indicated a positive relationship, while OR less than 1 indicated a negative relationship.

3. RESULTS AND DISCUSSION

3.1. Awareness and adoption levels of DAES

According to table 1, respondents showed the highest level of awareness (84.2%) and adoption level (68.8%) with mobile phone-based advisory services, such as SMS alerts, voice calls, and WhatsApp messages This means that mobile technology remains the most efficient and convenient channel for farmers to access agricultural information. It is highly popular since it can be cheap yet easy to use and has a broad network, even in rural areas. Arouna et al. (2020) and Ferrari et al. (2022) also reported the same finding and found that mobile phones have a significant role in informing smallholder farmers on how to treat crops, pests, and market prices in a timely manner. Nevertheless, despite the high adoption, the awareness-usage gap of 15.4 percent suggests that some farmers continue to experience low levels of technical literacy or low-quality services.

Table 1: Awareness and Adoption Levels of Digital Agri-Extension Services (n = 385)

Indicators	Awareness (%)	Adoption (%)	Rank
Mobile phone-based advisory services (SMS, Calls, WhatsApp)	84.2	68.8	1
Government agricultural apps (e.g., Punjab Agriculture Helpline)	72.5	54.5	2
Private agricultural apps (e.g., Agri-tech platforms)	65.4	42.1	3
Social media platforms for agricultural learning (e.g., Facebook, YouTube)	60.3	38.4	4
Online weather and market information services	58.7	36.1	5
Overall Awareness and Adoption Level	68.2	47.98	-

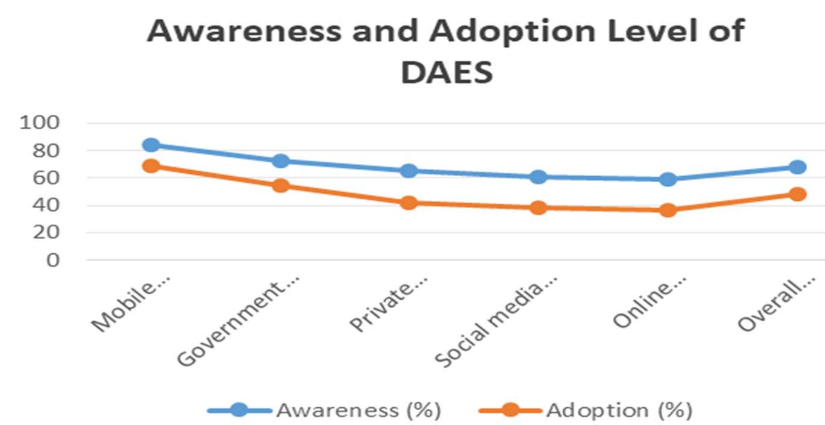

Fig 1: Awareness and adoption level of digital agri-extension services.

The second on the list is the Punjab Agriculture Helpline, whose awareness and adoption rate are 72.5% and 54.5%, respectively. This indicates the growing trust of farmers in online services offered by the government. However, nearly 18 percent gap between awareness and adoption suggests that there might be barriers like lack of training, low smartphone penetration and technical factors. The level of awareness and adoption in the case of private agricultural apps was 65.4% and 42.1% as also shown graphically in Fig 1, respectively. This may be due to credibility issues, subscription costs, and lack of advertising as Hoang (2020), Kieti et al. (2022) and Klerkx et al. (2022) discovered in their studies on digital agriculture adoption.

The lowest awareness and adoption rates were observed for social media platforms and online weather and market information services. The awareness of Facebook and YouTube were 60.3% and the adoption was 38.4%, signifying a substantial percentage of the farmers know about these media yet not alluse them as an avenue for learning about agriculture. This is consistent with Crastes dit Sourd (2023), who noted that the farmers are more of an entertainment platform than a source of farm information on social media. Similarly, weather and market information services on the internet registered the lowest awareness (58.7%) and (36.1%) adoption levels, which portrays a significant disconnection in access and knowledge. Their biggest shortcomings include poor internet connectivity, the lack of localized content, and poor digital literacy (Dollman et al., 2021; Fabregas et al., 2022; McCampbell et al., 2021).

The findings also show that of the 68.2% of farmers have heard about digital agri-extension services and only 47.98 of them have adopted. This 20% gap highlights the main challenges of confidence among farmers to work with digital tools, improving digital infrastructure, and farmers' digital literacy. Bridging this gap will help add value to digital extension services, leading to more informed decision-making, greater agricultural productivity, and sustainable agricultural development in Punjab.

3.2. Factors Influencing Adoption of Digital Agri-Extension Services

The results of a binary logistic regression analysis, undertaken to determine the socio-economic, institutional, and technological factors that predetermine the adoption of digital agri-extension services (DAES) by farmers in Punjab, Pakistan, are provided in Table 2. Adoption status is the dependent variable, with 1 assigned to adopters and 0 to non-adopters. The independent variables are key socio-economic traits, institutional support mechanisms and technological preconditions that are hypothesized to impact the choice of farmers.

Table 2 shows that the statistical value of the model was significant. The value of Nagelkerke R^2 was 0.512, meaning that the variables incorporated in the model explained 51.2 per cent of the variation in adoption behavior. The Hosmer and Lemeshow test also showed good model fit with a p-value of 0.478 and an overall prediction rate of 80.4% which signified its strength in terms of being able to distinguish between adopters and non-adopters.

Table 2: Binary Logistic Regression Results for Factors Influencing Adoption of Digital Agri-Extension Services (n = 385)

Variable	B	S.E.	Wald	Odds Ratio (Exp(B))	p-value
Socio-Economic Factors					
Age (years)	-0.024	0.011	4.79	0.976	0.029 **
Education level (years)	0.158	0.042	14.15	1.171	0.000 ***
Farm size (acres)	0.065	0.028	5.39	1.067	0.020 **
Monthly farm income (PKR)	0.000014	0.000005	8.12	1.000	0.004 **
Farming experience (years)	0.013	0.009	2.08	1.013	0.149
Institutional Factors					
Access to extension services (1 = Yes)	0.732	0.263	7.75	2.080	0.005 **
Participation in farmer groups (1 = Yes)	0.410	0.198	4.29	1.506	0.038 **
Access to credit (1 = Yes)	0.368	0.176	4.39	1.445	0.036 **
Technological Factors					
Mobile phone ownership	0.288	0.111	6.72	1.334	0.010 **
Smartphone availability	0.417	0.128	10.60	1.518	0.001 ***
Internet connectivity quality	0.396	0.122	10.54	1.485	0.001 ***
Perceived ease of use of apps	0.289	0.103	7.87	1.335	0.005 **
Perceived usefulness of services	0.452	0.117	14.89	1.571	0.000 ***
Constant	-4.263	0.921	21.40	0.014	0.000 ***

Statistic	Value
-2 Log-likelihood	342.78
Cox & Snell R^2	0.389
Nagelkerke R^2	0.512
Hosmer & Lemeshow Test (p)	0.478
Overall Prediction Accuracy	80.4%

Significance Levels

- *p < 0.001 (highly significant)
- p < 0.01 (significant)
- *p < 0.05 (moderately significant)*

One of the most significant predictors ($\beta = 0.158$, $p < 0.001$) was education level, with the odds ratio (OR) of 1.17. This finding aligns with (Munthali et al., 2022) who determined that educated farmers are more qualified to understand and apply digital technologies (Oliveira et al., 2020 and Klerkx and Rose, 2020). The size of farms had a positive and significant impact ($\beta = 0.065$, $p = 0.020$, OR = 1.067), as larger farms with more resources were better positioned to invest in new technologies. Similarly, the adoption was affected positively by farm income ($\beta = 0.000014$, $p = 0.004$) since more affluent farmers were able to purchase smartphones and internet services. Conversely, the age variable was discouraging ($\beta = -0.024$, $p = 0.029$, OR = 0.976), indicating that younger farmers were more inclined to accept digital tools. The same is also found by Ojo et al. (2020), Kumar et al. (2020) and Leng et al. (2020). Surprisingly, the difference in the farming experience was not statistically significant ($p = 0.149$), meaning that the experience alone cannot be directly linked to the rise in the adoption rates.

The institutional factors were also highly critical in making decisions to adopt. Access to extension services was one of the strongest predictors ($\beta= 0.732$, $p = 0.005$, OR = 2.080), showing that farmers with consistent access to extension services were more inclined to adopt DAES by twice the odds of those participants with no access.

This explains the relevance of the traditional extension in marketing of the digital solutions that are approved by Martey et al. (2021) and Ogwuike et al. (2021). Similarly, participation in farmer groups positively influenced adoption (β= 0.410, p = 0.038, OR = 1.506), meaning that peer learning and experience sharing are significant to jumpstart technology adoption. Access to credit has also become a significant parameter (β = 0.368, p = 0.036, OR = 1.445), meaning that financial support will help farmers to break the barriers, such as the cost of smartphones and data charges, as Paudel et al. (2021) and Porciello et al. (2022) indicate.

Technological factors were also of importance in adoption. The impact of the availability of smartphone was very high (β = 0.417, p = 0.001, OR = 1.518). Similarly, internet connectivity was another significant factor in adoption (β = 0.396, p = 0.001, OR = 1.485); therefore, there is a need to establish a stable ICT infrastructure in rural areas. The greatest impact was created by perceived usefulness of DAES (β = 0.452, p < 0.001, OR 1.571), suggesting that farmers with higher perceived usefulness and relevance of digital services were 57.1% more likely to adopt them. This observation aligns with the Technology Acceptance Model (Rodriguez et al., 2021; Sardar et al., 2020), which defines usefulness as one of the primary factors that drive technology use. Perceived ease of use also played a role (β= 0.289, p = 0.005, OR = 1.335) and it meant that easy and convenient platforms promote more adoption.

Overall, the results suggest that three determinants that affect the adoption of DAES are socio-economic preparedness, institutional backing, and access to technology. Education, perceived usefulness, smartphone ownership, and internet access and extension services were perceived to be the most highly influential. These findings demonstrate that the combination of policy interventions (i.e., improved rural ICT infrastructure, improved digital literacy programs, and financial incentives in order to bridge the gaps in adoptions) is needed. Similar statements have been put forward by Rodriguez-Sabiote et al. (2021) and Shang et al. (2021), who emphasize that digital transformation of agriculture requires technological innovation and socio-economic and institutional support.

3.3. Chi-Square Test Results

Table 3 presents the results of the Chi-square (χ^2) test, which was conducted to examine the association between various socio-economic, institutional, and technological variables and awareness status of digital agri-extension services among farmers in Punjab, Pakistan.

Table 3: Chi-Square Test Results for Associations between Socio-Economic Variables and Awareness Status (n = 385)

Variable	χ^2 Value	Df	p-value	Association
Education Level	24.738	3	0.000 **	Significant
Age Group	6.215	3	0.101	Not Significant
Farm Size Category	10.386	2	0.006 **	Significant
Farm Income Category	13.954	2	0.001 **	Significant
Access to Extension Services	20.482	1	0.000 **	Significant
Participation in Farmer Groups	8.254	1	0.004 **	Significant
Smartphone Availability	28.671	1	0.000 **	Significant
Internet Connectivity Quality	18.921	1	0.000 **	Significant

Note: p < 0.05 indicates a statistically significant association.
df = degrees of freedom.
Significance levels: *p < 0.05 = Significant, p ≥ 0.05 = Not Significant*

The results indicate a high level of correlation between the level of education and the awareness status (χ^2= 24.738, p = 0.000). This indicate that more educated farmers stand a higher possibility of being notified of the digital agricultural services. This is consistent with the past studies conducted by Ali (2021) and Shang et al. (2021) that determined that education improves the ability of farmers to access, process, and use agro information through digital channels. Similarly, awareness is also strongly correlated with the size of the farm (χ^2 = 10.386, p = 0.006), meaning that larger farms are more aware of the digital services compared to smaller farms, which could also be explained by their bigger resources and more significant need to learn about the updated farming methods.

Moreover, farm income was also a significant predictor of awareness (χ^2= 13.954, p = 0.001). a positively significant correlation with access to extension services (χ^2= 20.482, p = 0.000), indicating that the more frequent contact with extension agents, the more exposed and aware of digital tools the farmers are. This result aligns with that of Singh et al. (2020) and Smidt et al. (2021), who reported that extension services are very fundamental in respect to the awareness creation and adoption of modern agricultural technologies.

Participation in farmer groups could also be considered another factor that showed a significant association (χ^2= 8.254, p = 0.004). Farmer groups and cooperatives help in knowledge sharing and shared learning that informs the farmers about new innovations in technological advancements. Regarding technological aspects, the presence of smartphones had the greatest degree of importance (χ^2 = 28.671 = 0.000), as farmers who have access to smartphones stand a higher chance of being familiar with mobile-based agricultural advisory services. In line with this, internet availability had a significant correlation with awareness ($\chi^2 = 18.921$, $p = 0.000$), which confirms that the quality of internet access is a prerequisite to allow farmers to utilize digital extension services.

On the other hand, the age group did not have a significant value with the awareness ($p = 0.101$), indicating that the awareness does not always rely on the age of the farmer but on the availability of information and resources. Van Campenhout et al. (2021) and Voss et al. (2021) also discovered that younger and older farmers can be equally aware of having appropriate institutional and technological backup. Overall, these results suggest that a set of socio-economic (education, income, farm size), institutional (extension services, farmer groups), and technological (smartphone owner-ship, internet quality) moderators must be considered when explaining how farmers learn about digital agri-extension services.

4. CONCLUSION

The study concluded that the awareness about DAES was sufficiently good, but actual adoption was lower, indicating that there is a considerable gap between the awareness about the existence of digital services and the implementation in farming activities. Mobile phone based advisory services were observed to be the most utilized digital tool, because of the availability and affordability of mobile technology in rural areas. The result of the binary logistic regression model showed that the level of education, size of the farm, income, availability of smartphones, internet availability, and accessibility to extension services were powerful predictors of adoption of DAES. Further, perceived usefulness and ease of use were the most influential factors, underscoring the importance of designing convenient and easy-to-use digital platforms for farmers. The presence of institutional support was also significant in encouraging its adoption by increasing trust and reducing financial barriers. Results recommend that traditional extension services should be integrated with the digital platforms in order to expand the channel and effectiveness. Further, there is necessity of reinforcement of digital ecosystems through promotion of sustainable agricultural growth and rural transformation in Punjab.

Declarations

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Conflicts of Interest: The authors report no conflicts of interest.

Data Availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Ethics Statement: The study involving human participants was reviewed and approved by the Institute of Agricultural Extension, Education, and Rural Development, University of Agriculture, Faisalabad. All research procedures complied with relevant institutional and local ethical standards, and written informed consent was obtained from all participants before participation.

Authors' Contributions: Asghar Ali was responsible for the study conceptualization, methodology design, data collection, formal data analysis, preparation of the original draft, and manuscript review and editing.

Generative AI Statement: The authors declare that no generative artificial intelligence tools, including DeepSeek, were used in the preparation of this manuscript.

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