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Drivers and intensity of adoption of digital agricultural services by smallholder farmers in Ghana

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A R T I C L E I N F O

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A B S T R A C T

The penetration of digital technologies to enhance market participation by farmers, and intensify farmers' access to support services such as finance, farm inputs, and agricultural production information is on the rise in developing countries. However, the drivers and intensity of the adoption of these technologies by Ghanaian farmers have received little attention in policy and academic circles. This study analyzed the factors that drive the adoption and intensity of adoption of digital agricultural solutions by smallholder farmers in the Bono East Region of Ghana. The study used a survey questionnaire to collect data from 1199 randomly selected smallholder farmers in 2023. The multivariate probit model and the Heckpoisson regression model were used to analyze the drivers of different digital agricultural solutions and the intensity of adoption of these solutions, respectively. The results show that there is a joint demand for technologies that enhance access to extension services and those that accelerate access to inputs. Market-oriented solutions and agricultural extension solutions exhibited a complementary relationship. In addition to selected socio-demographic factors, the study found that membership in farmer-based organizations, access to credit, and participation in agronomic training increased farmers' propensity to adopt different digital agricultural solutions and increased the number of solutions adopted by farmers. Receiving visits from extension officers reduced the likelihood and intensity of adopting digital agricultural solutions. The results suggest that government and development partners should enhance access to credit and promote capacity development programmes among farmers. This will capacitate them to adopt digital agricultural solutions.

1. Introduction

The development of agriculture in the global south has undergone considerable technological transformation over the years. Among this technological transformation in the agriculture sector is the rapid introduction and adoption of digital agriculture. The World Bank in 2022 reported that long-term economic development is anchored on the adoption of new technologies [1]. According to the Technical Centre for Agriculture and Rural Cooperation (CTA) [2], there are more than 390 digital agricultural service providers in Africa. In addition, a recent digitalization report from the CTA in 2019 revealed that 33 million smallholder farmers in Africa are currently reached by digital applications and this is projected to reach 200 million by 2030. These applications are diversified and

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come in the form of advisory and information services, market linkages, financial access, and supply chain management, with advisory and information services dominating the market [2]. By January 2020, the Global System for Mobile Association (GSMA) under the digital agriculture technology programme had tracked about 437 digital agricultural services in Sub-Saharan Africa [3]. Technological development in the telecommunication industry is largely responsible for the sharp growth in the number of digital agricultural companies. There has been an increase in the use of mobile devices globally from 2 billion to 5 billion and it is projected to reach 5.9 billion by Refs. [4,5]. Despite this growth in digital devices in Africa, less than 10% of farmers have access to these digital devices [6]. In Ghana, the number of mobile phone connections increased by 2.6 million (+6.2%) between 2021 and 2022 [7]. The Internet penetration rate in Ghana stood at 68.2% of the total population in 2022 [7]. As a result of this development, some smallholder farmers now have access to digital devices such as mobile phones and tend to use them for agricultural activities. By digital agricultural solutions, we mean everything (TV, radio, sensors, and mobile phone) that delivers farming advice via text messaging to interactive voice response. These solutions in Ghana are usually provided by Agritech startups such as Esoko, Farming, Farm Radio, and Trotro Tractor through Audio, video content, and SMS. The solutions comprise mobile-accessible apps and services that provide timely market price data, financial services, weather prediction, information on pest outbreaks, and supply chain management services [8]. Generally, the solutions given to smallholder farmers are mainly information/advisory and link farmers to markets (inputs and output) [9] (see Figs. 1 and 2).

According to Trendov et al. [10], the world is experiencing a digital agricultural revolution that could help meet the food needs of the world. As a result, its adoption is expected to address the numerous challenges that smallholder farmers face in their farming activities [11]. Some of these challenges include limited access to credit, poor farming decisions due to unpredictable weather, limited access to market information, and transportation of products from the farm location to the market. Adopting digital agriculture solutions presents an opportunity for farmers to increase crop yield, reduce cost, and enhance food security. In the case of smallholder farmers, digital agricultural solutions would address their needs by providing greater access to credit and remunerative markets. Its intense adoption could integrate farmers into the global production system by ensuring traceability, and transparency, and reduced transaction costs [12]. Digital agriculture would therefore increase crop yield, reduce cost, and improve agricultural sustainability and food security [13].

Despite the potential benefits of digital agricultural solutions to smallholder farmers, the adoption of digital agriculture solutions is still low in many parts of the world, especially in the Global South. For instance, Goedde et al. [14], argue that only 30 % of farmers in Sub-Saharan Africa apply digital agricultural solutions. Although digital agriculture al solutions are increasingly spreading across Ghana, adoption by smallholder farmers is low [9]. This raises questions about the factors that could influence the adoption of these solutions by farmers. In the same vein, these solutions could reduce information asymmetry among smallholder farmers in the Bono East region of Ghana since farming in this area is inherently risky, and farmers contend with risks and opportunities arising from access to land, credit, markets, and vagaries of nature. Shocks such as drought and disease annually undermine the productive capacity of the

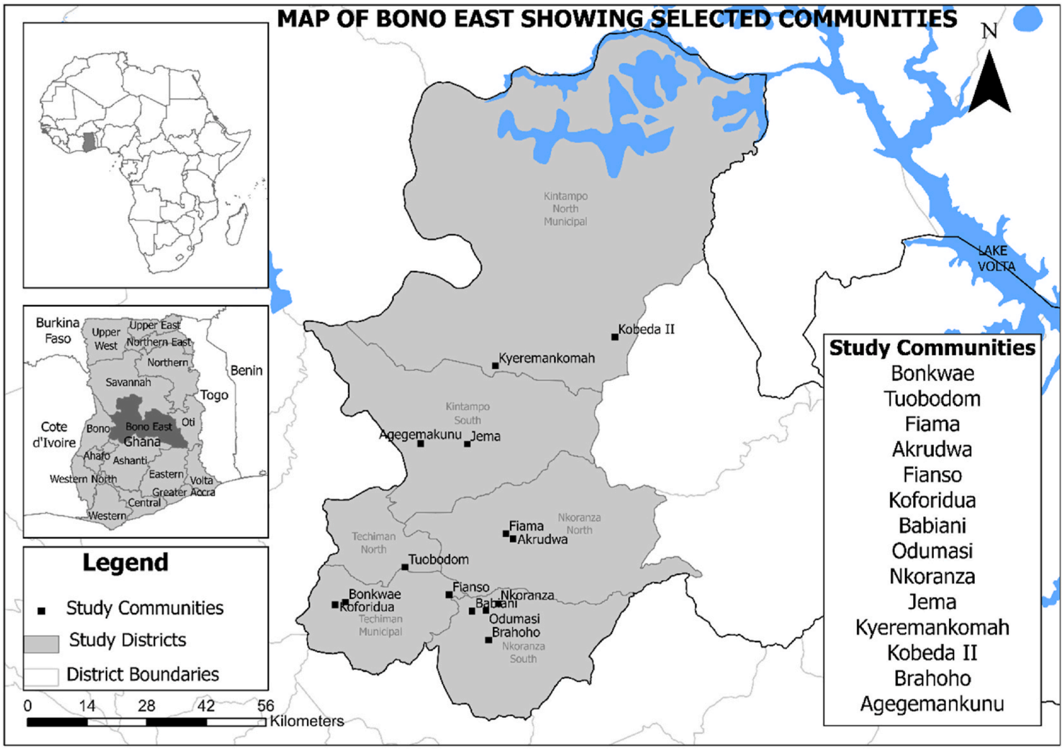

Fig. 1. Map of Bono East showing the study area.

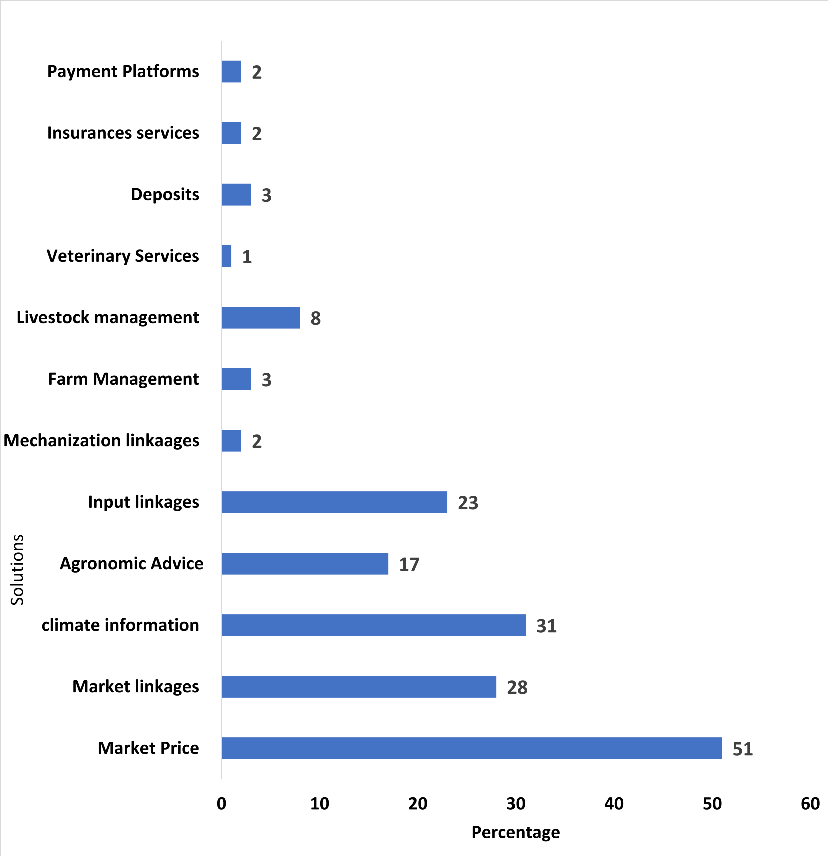

Fig. 2. Types of digital agricultural solutions adopted by farmers in the study area.

farmers. These challenges exist despite the implementation of Ghana's rural telephony and digital inclusion programmes and other digital technology solutions in the Bono East Region. Furthermore, a large number of the digital solutions provided to smallholder farmers in the region remain largely subsidized. This study therefore aims to provide empirical evidence on the factors that influence the adoption of digital agriculture by smallholder farmers solutions in the region.

Studies on the adoption of digital agricultural solutions are still developing [15]. Whereas some studies [16,17] have focused on digital agricultural technologies including robotics and precision agriculture, little attention has been given to the adoption of digital agricultural solutions such as market-oriented solutions, financial solutions, and extension-oriented solutions, and solutions that enhance access to farm inputs by smallholder farmers in developing countries. Some studies have attempted to address farmers' adoption behaviour by focusing on particular solutions such as extension-oriented solutions [9], financial-oriented solutions [18], and market-oriented solutions [19] in isolation. Meanwhile, the adoption of these solutions is not mutually exclusive. Although Abdulai et al. [20] looked at the factors that influence the likelihood of the adoption of digital services by farmers, they do not examine the intensity of the adoption as well as the simultaneous adoption of digital agricultural solutions. Meanwhile, knowledge of the complementarity and substitutability of these solutions is necessary to focus on combinations of solutions that maximize the utility of farmers. This knowledge is still scanty in literature. Thus, we extend the literature on the adoption of digital agricultural solutions by applying the multivariate probit model to assess farmers' simultaneous adoption of multiple digital agricultural solutions. Further, we employed the Heckpoisson model which addresses endogeneity to assess the intensity of adoption of the different agricultural solutions.

The rest of the paper is organized as follows: Section 2 presents a review of the literature on the adoption of agricultural technology; while Section 3 presents the methods of data collection and analysis. Section 4 presents the results and discussion; and finally, Section 5 concludes the paper with policy implications.

2. Literature on the adoption of digital agriculture

The digitalization of agriculture in the Global South has received considerable attention from researchers. The proliferation of mobile phones, radio, TV, and other technological devices is largely responsible for the ascendency of digital agriculture solutions.

According to Walter [21], the drivers of the adoption of digital agricultural solutions are within three main dimensions (who, why, and where). The 'who' context includes the characteristics of the farmers and the farm's structural characteristics, the 'where' context includes spatial and institutional characteristics and the "why" dimension looks at the motivation for adopting the innovation. These dimensions are summarized by the diffusion theory as individual, innovation, and contextual characteristics [22]. The individual characteristics (sociodemographic) focus on individual differences or traits that predispose the adopter to adopt the technology. The innovation characteristics are specific to the innovation (digital agriculture technology) and this deals with how it is used and how digital agriculture is compatible with the lifestyle of the farmers. The third characteristic looks at the contextual characteristics that make the environment and surroundings (institutional).

Sociodemographic variables are recalled frequently when analyzing the adoption of agricultural technology [23]. Ayisi et al. [24] emphasize the importance of socio-demographic factors such as age, educational status, gender, and marital status in the adoption of agricultural technologies. The works of Abdulai et al. [20] identified farmer characteristics, digital competencies, and access to digital resource as crucial in determining farmers' participation in digital agricultural services. Specifically, Workie and Tasew [23] argued that younger farmers are more motivated to adopt new technologies than older farmers due to their higher educational levels. Older framers, on the other hand, are generally expected to compensate with high levels of experience and informal knowledge [25]. However, some empirical studies have found that older farmers adopt technology. Higher-income farmers are also generally more inclined to accept and use technology [26]. The higher-income farmers also depend on their access to credit facilities and the output of their products in a farming season. Increased output and increased access to credit for the farmer could lead to the adoption of innovation by farmers. Even though some digital agricultural solutions are often advertised as free, they often come with hidden costs. Such solutions could offer limited features and services in the free version. After farmers adopt the solution, they would have to adhere to strict farming practices or risk losing access to extension services provided by the solutions. This could influence the adoption of the innovation/technologies because such an adaption has the potential to increase farmers' cost of production. As a result, lower-income earners who cannot afford would not be inclined to adopt the innovation. Income level as a variable could therefore influence the adoption and the intensity of the adoption of agricultural technologies [27].

Another group of variables that have also received attention in the discourse of agricultural innovation are farm characteristics such as location, size, and soil productivity. These farm characteristics vary across space and over time [28]. According to Masi et al. [29], larger farm owners are generally more likely to adopt new technology due to access to credit and higher labour costs. Similarly, access to information has a significant impact on technology adoption [30]. This implies that the remoteness of a farming area may limit the availability of information; however, once the technology is introduced the farmer may readily adopt it if it is perceived as beneficial to the farmers' production process. Another group of variables of concern to the adoption process are institutional factors such as group membership, access to training, and access to credit. Mutungi et al. [31] found that group membership and training are important factors that affect the adoption of post-harvest technology in Tanzania Maize farmers. This is because group membership enhances social capital that allows trust and information exchange. This could influence the decision of a farmer to adopt a particular technology. This finding is contrary to the finding of [32], where group memberships did not have any influence on technology adoption. Access to credit has a significant effect on farmers' decision to adopt a particular technology and variety of crops to cultivate [33]. The aforementioned factors could add to or reduce the intensity of the adoption of agricultural technology such as digital agricultural solutions.

The review of theoretical and empirical literature has revealed the variables that can influence the adoption of digital agricultural solutions by smallholder farmers in the Bono East region of Ghana. From the empirical review, it can be realized that most of the studies on the adoption of agriculture technology have often concentrated on the introduction of new crops (seeds), chemicals (pesticides), new farm implements, and in a few cases on specific digital technology such as Mobile Money. For instance, although a recent study by Abdulai et al. [20] was on digital agriculture, their study focused on the participation is changing farmers' experiences. Also, the study was limited to only three digital services provided (Esoko Ghana, Farm Radio International, and agrocenta). Our study extends to all other solutions provided by digital companies, CSOs, NGOs, and state institutions such as MOFA. In addition, smallholder farming in the Bono East region is a complex production system that is characterized by diverse crops and livestock production as such it is expected that farmers would adopt diverse solutions in the production process. Little in terms of drivers and the intensity of adoption is however known about the adoption of digital agricultural solutions among smallholder farmers in the Bono East region. This paper intends to address such gaps in the literature.

3. Methods

3.1. Study area

The Bono East Region lies in the centre of Ghana and covers an area of 33,654.54 km^2, representing ten percent (10 %) of Ghana's total land size [34]. The region has a bimodal rainy season, with the first beginning in June and the second beginning in September coupled with the fertile soil which is suitable for agricultural activities. The land is generally flat which is suitable for crop production like yam, maize, and groundnut [34]. Agriculture employs a majority of the people in the region. The region has a lot of migrant farmers in its rural communities. According to the Bono East Regional Coordinating Council [34], the region is predominantly agrarian and well-noted for the cultivation of cereals and tubers. The major crops grown are food crops such as yams, potatoes, maize, cassava, cocoyam, and plantain. Vegetables like tomatoes, garden eggs, onions, and okra are also cultivated in the region. Some farmers in parts of the region grow cash crops like cocoa, cashews, mango, oranges, cowpeas, and groundnut. These features make the region attractive for the implementation of agricultural policies and the deployment of digital agriculture solutions by companies such as Frameline and Esoko. The area was chosen for the study due to the high presence of Agriitech companies in the region that deploy several digital agriculture solutions to smallholder farmers in various forms. In addition, two of Ghana Rural Telephony and Digital Inclusion

Programme (GRT&DIP), and one Cyberlab are located in the region. The project is implemented by the Ghana Investment Fund for Electronic Communication to improve access to ICT in underserved communities in the region. Moreover, government programmes such as the Block Farm and Planting for Food and Jobs have been implemented there.

3.2. Sampling and data collection

The study used a three-stage sampling procedure to select participants for the study. The first stage involved the purposive selection of six (6) districts in the region. These districts were selected due to the dominance of the operations of agricultural technology firms, non-governmental organizations that promote agricultural development, and government extension offices. In the second stage, communities where agricultural production activities dominate were identified with the help of agricultural extension officers who were employed as field officers. Upon identification of these communities, and with the assistance of these officers, out of these communities, 16 of them were randomly selected. After households whose main economic activity was farming were identified and randomly selected. Farmers were surveyed at their homes since there was farming activity going on during the survey period. Most farmers were therefore found in their homes. This formed the second stage of the sampling procedure. Finally, the proportional-to-size technique was applied to select farmers from the identified communities. The eligibility criteria were that the unit of data collection was only farmers who were 18 years and above. These farmers must also have lived in the community during the last farming season in 2022. In all the total sample size of 1199 was interviewed. Extension officers were recruited as enumerators and were trained to carry out the administration of the interview schedule. The survey was conducted in 2023.

A survey questionnaire was used to collect data from the selected smallholder farmers in the Bono East Region. The data collected included household and farm characteristics, questions on digital agricultural technologies and companies to which farmers were exposed, and institutional support services were also asked. The surveyed questionnaire was configured in Computer-Assisted Personal Interviews (CAPI) using Kobo Collect. The data collection exercise consisted of three teams who were supervised by the first author of the study and some colleagues from the University of Cape Coast, Ghana. Before data was collected informed consent was obtained from all participants for the study and they were also assured of anonymity. In addition, an ethical clearance was taken from the University of Cape Coast ethical review board. This was done to ensure that the researcher adhered to accepted ethical standards as well as to protect the rights, dignity, and welfare of participants.

3.3. Analytical framework

We analyzed farmers' adoption of digital agricultural solutions in Ghana. Farmers in Ghana are exposed to different agricultural solutions which can be categorized under four main themes including market-oriented solutions, finance-oriented solutions, and solutions that are intended to enhance access to agricultural inputs and extension services. According to Ref. [35] the adoption of these solutions can accelerate progress toward solving the challenges that limit the productivity of farmers in sub-Saharan Africa. We argue that the removal of all barriers to the adoption of these technologies is crucial in ensuring that farmers gain access to improved agricultural services in the face of poor infrastructural and institutional development. We also argue that when farmers are employed through the adoption of multiple digital agricultural technologies, they can maximize gains from agricultural production. Thus, following the random utility theory, a rational farmer will adopt a digital agricultural solution to maximize his/her utility. This utility can derive from the benefits accrued from the adoption of this solution. The utility *U* that the *ITH* farmer can derive from adopting a digital agricultural solution can be expressed as a linear sum of the deterministic component *Vi* and a random term that represents the observable and the unobservable components of the utility, respectively. The utility can be expressed as (Equation (1))

$$U_i = V_i + \varepsilon_i \tag{1}$$

3.3.1. Modelling the drivers of adoption of different digital agricultural solutions

The study used the multivariate probit model (MVP) to analyze the factors that influence the uptake of different digital agricultural solutions by farmers in the Bono East Region of Ghana. The choice of different digital agricultural solutions is not mutually exclusive. That is, farmers can concurrently choose more than one digital agricultural solution or replace other solutions with others. Thus, we used the multivariate probit (MVP) model to estimate the choice of different digital agricultural solutions by farmers in Ghana. The model allows for the potential correlations between the error terms and the relationship between the adoption of different digital agricultural solutions. Complementarity and substitute associations between the solutions are one of the main sources of correlations [35]. When digital agricultural solutions are used as complements, then it implies that they are used together. The marginal benefits of each solution increase as the other also increases. For instance, the ability to access market solutions could lead to the adoption of input solutions. In the same vein, a farmer may feel that adopting an input solution is useless if he cannot access weather information. A complement therefore lifts the farmer's ability to adopt or not adopt a solution. Substitution effect on the other hand means that some digital solutions are adopted in place of other technologies. For instance, a farmer who adopts a market-oriented solution might replace it with an extension service solution due to factors such as cost, training, and age of the farmer. Based on this we modeled the drivers of the adoption of digital agriculture solutions as follows.

Let digital agricultural solutions be defined as $(j = M, F, I, E)$ where *M* represents market-oriented digital agricultural solutions, *F* is finance-oriented solutions, and *I* and *E* represent digital agricultural solutions that enhance access to inputs and extension services, respectively. A farmer is faced with the decision to adopt from the set (*j*). Following the utility theory, adoption is realized when the net benefit is greater than zero, $T_{ij}^* = E[U(\pi_A)] > E[U(\pi_N)]$. The net benefit T_{ij}^* which a farmer derives from the adoption of *jth* digital agricultural solution is a latent variable that is determined by household and farm characteristics, institutional characteristics (X_i), and the error term μ).

This is given by Equation (2):

$$T_{ij}^{*} = X_i^{'}\delta_j + \mu_i (j = M, F, I, E) \tag{2}$$

The unobserved preferences in Equation (2) translate into the observed binary outcome equation for each choice based on the indicator function given by Equation (3):

$$T_{ij} = \begin{cases} 1 \; if \; T_{ij}^{*} > 0 \\ 0 \; otherwise \end{cases} \tag{3}$$

In the MVP model where farmers can adopt several digital agricultural solutions, the error terms follow a multivariate normal distribution (MVN) with zero conditional mean, and variance normalized to unity (for identification of the parameters), where (μ_F, μ_P, μ_H, μ_C, μ_W) → *MVN(0, Ω)* and the symmetric covariance matrix Ω (nxn correlation matrix). The unobserved correlation between the stochastic components of the various digital agricultural solutions is represented by the non-zero off-diagonal elements in the covariance matrix. This correlation coefficient defines the links between digital agricultural solutions that are complementary (positive correlation) and substituting (negative correlation).

3.3.2. *Modelling the drivers of the intensity of adoption of digital agricultural solutions*

In this study, adopting digital agricultural solutions is considered as a two-step decision-making process. In the first stage, farmers will have to choose to adopt digital agricultural solutions, and in the second stage decide on the number of digital agriculture solutions to adopt. When the farmer decides to adopt digital agricultural solutions then the observation is one (1) and when the farmer does not adopt then Zero. Contingent on the first stage, the number of digital agricultural solutions adopted is then treated as count data. Combining stages one and two gives a Heckpoisson model that uses a binary probit and Poisson regression models to control for the bias caused by sample selection by simultaneously estimating parameters of binary and count data [36] accordingly, we use a Heckpoisson model to assess the drivers in the adoption of digital agricultural solutions due to its ability to fit outcomes of count data and correct for sample selection biases. The model also uses the likelihood estimator thereby relaxing the assumption of equidispersion contrary to the standard Poisson model.

The model is estimated in two parts; the selection (probit) and intensity models (Poisson) as in equations (4) and (5).

The selection model:

$$S_j = \left\{ \begin{array}{c} 1 = adopts \; digital \; agriculture \\ 0 = otherwise \end{array} \right\}$$

$$S_j \left\{ \begin{array}{c} 1, if \; X_i^{'}\beta + \varepsilon_{1i} > 0 \\ 0, if \; otherwise \end{array} \right\} \tag{4}$$

$$\text{Intensity model} : P_i = X_i^{'}\beta + \varepsilon_{2i} \tag{5}$$

Table 1
Description of explanatory variables included and hypothesized signs.

Variable	Description	Measurement	Sign
Age	Age of the farmer in years	Continuous	+/−
Ln (wages)	Log of wages paid to farmworkers in Ghanaian Cedis	Continuous	+
Migratory Status	Migratory status of the farmer	Dummy: 1 = migrant; 0 = otherwise	+/−
Household head	The farmer is the head of the household	Dummy: 1 = Yes; 0 = otherwise	+
Ln (schooling years)	Log of number of years farmers had of formal education	Continuous	+
Ln (farm size)	Log of farm size in acres	Continuous	+
Gender	Sex of farmer	Dummy: 1 = male; 0 = female	+/−
Ln (income)	Log of total household income in Ghanaian Cedis	Continuous	+
Credit access	Whether the farmer had access to credit from a financial institution/farmer group/friends in the past 1 year	Dummy: 1 = Yes; 0 = otherwise	+
Group membership	Whether the farmer is a member of a farmer-based organization	Dummy: 1 = Yes; 0 = otherwise	+
Extension visit	Whether the farmer was visited by an extension officer in the past 1 year	Dummy: 1 = Yes; 0 = otherwise	+/−
Training	Whether the farmer participated in any training related to farming	Dummy: 1 = Yes; 0 = otherwise	+/−
Marital status	Whether the farmer is married	Dummy: 1 = Yes; 0 = otherwise	+

Note: US$ 1 = GHS 10 at the time of the study.

Where:

S_j is the binary indicator showing whether a farmer adopts digital agricultural solutions or not.

P_i is the number of digital a solution adopted showing the intensity of the adoption

$X_i^{'}$ are the explanatory variables hypothesized to influence the adoption of digital agricultural solutions

β is the vector of parameters to be estimated.

Equation (4) is the selection part of the model and is applied in assessing the drivers of digital agricultural solutions. The indicator S is always observed and takes the value 0 or 1, depending on whether the farmer adopted digital agricultural solutions or not. The second part of the model (equation (5)) is used to assess the factors influencing the intensity of the adoption of the digital agricultural solution (the intensity indicator P is only observed if S = 1). The indicator for the count outcome is observed if S = 1.

3.3.3. Description of variables and hypothesized signs

Table 1 presents the description of explanatory variables that were included in the econometric models. These variables were selected based on previous studies on factors that influence the adoption of agricultural technology [10,15,19,20,22,23,37–40]. These studies identified similar variables that influence the adoption of agriculture technology however these studies have focused on Land management, machinery, agrochemicals, and biotechnology in the agriculture sector. However, our study is on the adoption of digital agriculture solutions and we are interested in how the selected variables (sociodemographic, institutional) drive the adoption and the intensity of the adoption process. For instance, age is a proxy for resource endowment [41]. It is therefore expected that older farmers can't afford the costs of adopting agricultural technologies. On the other hand, younger farmers are risk-lovers whereas older farmers are risk-averse, thereby increasing the propensity of adoption by the former. Likewise, male farmers in developing countries have more access to resources, thereby enhancing their ability to afford new agricultural technologies. The study hypothesized that males are more likely to adopt agricultural technology. Married farmers can pool resources to advance access to agricultural technology. The study expects a positive relationship between marital status and the adoption of digital agricultural technologies. Farmers with high incomes and those who pay higher wages are expected to be high investors in agricultural production. Thus, we hypothesize a positive relationship between wages and the adoption of digital agricultural solutions. Migrants are temporary farmers and might not be inclined to invest heavily in agricultural production, hence a hypothesized negative relationship between migratory status and digital agricultural solutions. Education increases knowledge and understanding. It is therefore expected that more educated farmers can understand the requirements of effectively adopting agricultural technologies. Farmers with large farm sizes are more likely to adopt solutions that can enhance agricultural productivity. The study hypothesized that an increase in farm size will lead to an increased propensity to agricultural technologies.

We hypothesize that access to institutional support services can positively influence the adoption of digital agricultural solutions. We expect a positive relationship between access to credit and the adoption of digital agricultural solutions because access to credit enhances the resource endowment of farmers. Farmers who are members of groups are easily aware of digital agricultural solutions which increases their tendency of adopting such solutions. We, therefore, hypothesize a positive relationship between group membership and the adoption of digital agricultural solutions. Farmers who received extension visits and agronomic training are expected to understand the importance of digital agricultural solutions, thereby increasing the likelihood of adopting such technologies. The variables in Table 1 were selected based on the review of available literature and the practical importance of these variables.

Table 2
Descriptive statistics on the adoption of digital agricultural solutions.

Variable	Pooled		Male (n = 828)	Female (n = 371)	
Categorical variables	Frequency	Percentage			χ2
Dependent variables					
Market-oriented solutions (Yes)	653	54 %	74 %	26 %	13.29***
Finance-oriented solutions (Yes)	50	4.17 %	74 %	26 %	0.59
Input access solutions (Yes)	357	30 %	68 %	32 %	0.23
Extension access solutions (Yes)	388	32 %	65 %	35 %	3.98**
Explanatory variables					
Marital status (Married)	983	81 %	70 %	30 %	3.91**
Household head (Yes)	794	66 %	90 %	10 %	467.50***
Migratory status (Migrant)	769	64 %	74 %	26 %	28.45***
Credit access (Yes)	684	57 %	73 %	27 %	12.17***
Group membership (Yes)	624	52 %	76 %	24 %	29.02***
Extension visit (Yes)	576	48 %	76 %	24 %	25.30***
Training (Yes)	640	53 %	75 %	25 %	22.69***
Continuous variables	**Mean**	**Standard deviation**	**Mean (A)**	**Mean (B)**	**Diff (A–B)**
Age	43.02	11.99	44.36	40.05	4.32***
Wages	824.16	1093.95	855.02	755.30	99.73
Years of schooling	9.14	5.10	9.65	8.0	1.65***
Farm size	10.95	10.31	12.25	8.02	4.23***
Household income	1287.67	963.23	1371.88	1099.73	272.15***

Note: ** and *** represent statistical significance at 5 % and 1 % levels, respectively. GHS 1 = 10 at the time of the study.

4. Results

4.1. Digital agricultural solutions adopted by smallholder farmers

Table 1 presents descriptive statistics of the specific agricultural solutions adopted by farmers in the Bono East region of Ghana. A majority (50 %) of the farmers adopted digital agricultural solutions that enhance access to digital information about market prices. This implies that this solution is the most preferred solution by agricultural producers in the region. Other important digital agricultural solutions included the ones that provide weather information (31 %), link farmers to buyers (28 %) and input suppliers (23 %), and advise farmers on good agronomic practices (17 %). Digital solutions that were least adopted by farmers included solutions that linked farmers to highly mechanized inputs (2 %), provided digital solutions on farm management (3 %), livestock management (8 %), veterinary services (1 %), and financial services including insurance as well as payment platforms (4 %). The low adoption of these digital agriculture solutions could be explained by the size of the operation (less than 5ha) and the existence of mobile money services which negates the need for other agricultural solutions that are intended to promote access to finance.

The digital agricultural solutions adopted by farmers were grouped based on their perceived purpose or function. For instance, production-related information such as weather information from a digital agriculture company via any digital device was categorized under extension-oriented solution. Likewise, output price information is classified as a market-oriented solution since this information is intended to improve market participation. From this process, the digital agriculture solutions were grouped into four. These are market-oriented solutions (market price, and market linkage), finance-oriented solutions (financial services, insurance services, and payment platforms), input access solutions (input linkage, and mechanization linkage), and extension-oriented services (climate information, agronomic advice, farm management, livestock management, and veterinary services). Table 2 presents the results of the rate of adoption of digital agricultural solutions and characteristics of farmers, farm characteristics, and access to institutional support services, disaggregated along gender lines. The adoption rate of market-oriented solutions was the highest (54 %) whereas the adoption of finance-oriented solutions was the lowest (4 %). More males (74 %) than females (26 %) adopted market-oriented solutions. The adoption of solutions that enhance access to extension services was higher among males (65 %) than females (35 %). This shows a gender gap in the adoption of digital agricultural solutions.

All the explanatory variables favoured men. The results show that 81 %, 66 %, and 64 % of the respondents were identified as married, household heads, and migrants, respectively. The results reveal that the majority of the respondents had access to credit from financial institutions (57 %) and were members of farmer-based organizations (52 %). Extension visits were low since less than half of the respondents' received visits from agricultural extension officers. However, 53 % of the respondents had participated in agronomic training.

Table 3
Estimates of multivariate probit model of the determinants of uptake of digital agricultural solutions.

Variable	Market solutions	Financial Solutions	Inputs solutions	Access to extension
Age	−0.024	0.127	−0.482***	−0.059
	(0.205)	(0.435)	(0.186)	(0.191)
Ln (wages)	−0.005	−0.091	−0.004	0.096***
	(0.027)	(0.057)	(0.024)	(0.026)
Migratory Status (Migrant)	−0.044	0.010	−0.692***	−0.708***
	(0.108)	(0.196)	(0.099)	(0.106)
Household head (Yes)	0.003	−0.251	0.026	−0.138
	(0.160)	(0.264)	(0.151)	(0.168)
Ln (schooling years)	0.257	−0.231	0.268	0.260
	(0.189)	(0.266)	(0.176)	(0.181)
Ln (farm size)	−0.118	0.608***	−0.544***	−1.045***
	(0.074)	(0.126)	(0.070)	(0.080)
Gender (Male)	0.036	−0.254	0.055	0.300*
	(0.145)	(0.248)	(0.138)	(0.158)
Ln (income)	0.252**	0.465***	0.663***	0.719***
	(0.110)	(0.178)	(0.099)	(0.111)
Credit access (Yes)	1.388***	−0.938***	0.459***	1.218***
	(0.134)	(0.265)	(0.138)	(0.148)
Group membership (Yes)	0.582***	0.926**	0.112	0.362***
	(0.133)	(0.411)	(0.132)	(0.148)
Extension access (Yes)	0.191	−0.029	−0.377***	−0.754***
	(0.119)	(0.215)	(0.117)	(0.132)
Training (Yes)	0.647***	1.301***	0.937***	0.429***
	(0.138)	(0.453)	(0.136)	(0.152)
Marital status (Married)	0.120	−0.043	0.551***	0.321**
	(0.147)	(0.285)	(0.140)	(0.146)
Constant	−3.587***	−6.564***	−3.873***	−5.354***
	(0.185)	(2.045)	(0.965)	(1.059)
Observations: 1199	Likelihood ratio test: Wald $\chi2$ (52): 1173.86	Log-likelihood: −1398.0633	AIC = 2920.127	BIC = 3235.66

Notes: *, **, and *** represent statistical significance at 10 %, 5 %, and 1 % levels, respectively. US$ 1 = GHS 10 at the time of the study.

Male farmers were older than female farmers with average ages of 44 years and 40 years, respectively. On average, farmers paid GHS 824 to their farmworkers per month. This wage is above the minimum wage of Ghana which is GHS 446 per month as of 2023. Males had more years of schooling than females. On average, males had 9.65 years of schooling whereas females had 8 years of schooling. Following Ghana's education system, this implies that on average, male farmers have completed the senior high school level of education whereas the average female farmer has not completed this level of education. The results show that on average, males had a higher household income and larger farm sizes. The mean farm size of male farmers was 12.25 acres whereas that of females was 8.02 acres. This shows that women have relatively low access to productive resources such as land.

4.2. Drivers of uptake of digital agricultural solutions among farmers in southern Ghana

The study used a multivariate probit model to analyze the factors that influence the uptake of different agricultural solutions among smallholder farmers in Southern Ghana. The results are presented in Table 3. The fitness of the multivariate probit model was tested using the Likelihood Ratio (LR) test, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). The LR test based on Wald-Chi-square of 1173.86 ($p < 0.01$), the AIC and BIC of 2920.127 and 3235.66, respectively indicate that indeed the multivariate probit model fits the data set. The results show that sociodemographic characteristics, farm characteristics, and institutional factors influence farmers to use different digital agricultural solutions.

The results show a negative relationship between age and the adoption of digital solutions that relate to access to inputs. Older farmers were 48% points less likely to adopt input-related solutions. This could be because age is a proxy for access to resources and wealth, thereby reducing the propensity of older people to adopt solutions related to inputs given that they might already have such inputs. On the other hand, older people are risk-averse and are less likely to adopt modern technology [40]. The migratory status of the farmer was another demographic factor that influenced the adoption of digital solutions. The results show that migrants were 69 % and 71 % less likely to adopt input-related solutions and extension-related solutions, respectively. Marital status positively influenced farmers' decisions to adopt input-related solutions and extension-related solutions. Farmers who were married were 55 % and 32 % more likely to adopt input-related solutions and solutions that enhance access to extension services, respectively. Along gender lines, the results show that males were 30 % more likely to adopt digital agricultural solutions that enhance access to agricultural extension services.

Wages paid to farm workers were positively related to the adoption of extension-related solutions. Farmers who paid higher wages were about 10% points more likely to use extension-related digital solutions. This could be because these farmers are wealthy and could afford to patronize solutions that enhance access to extension services. In the same vein, the log of household income was positively related to the adoption of all digital agricultural solutions. Specifically, wealthier households were 25 %, 46 %, 66 %, and 72 % more likely to adopt market-related solutions, digital financial solutions, input-related solutions, and solutions that enhance access to extension services, respectively. This is because these households can afford the charges that are associated with the uptake of these digital solutions. The differences in degrees of the propensity of adoption show that wealthy households might already have access to markets and have relatively less need for financial solutions. On the other hand, their endowment could permit them to acquire more inputs and extension services. Farmers with larger farm sizes were 61 % more likely to adopt digital financial solutions. On the other hand, farmers with smaller farm sizes were more likely to adopt input-related solutions and extension-related solutions. Farmers with larger farm sizes would require access to finance to procure approved inputs which would translate to increased productivity.

Institutional factors including access to credit, membership in farmer-based organizations, access to agronomic training, and access to extension services influence farmers' adoption of digital agricultural solutions. Farmers who had access to credit were more likely to adopt market-related solutions and solutions that enhanced access to inputs and agricultural extension services. On the other hand, farmers who accessed credit were 94 % less likely to adopt financial-related solutions. This result is intuitive as farmers who had received credit from banks and relatives have enhanced resource endowment and do not need digital financial solutions which are even associated with transaction costs. Group membership was positively related to access to market-oriented solutions and digital solutions that enhance access to finance and extension services. Being a member of a group increased the probability that farmers would adopt market-related solutions, financial-related solutions, and extension-related solutions by 58 %, 93 %, and 36 %, respectively. The low demand for extension-related solutions could be because farmers who belong to groups are more likely to benefit from capacity development programmes that capacitate them with knowledge of good agricultural practices.

Access to extension services was measured by whether or not farmers received extension visits from agricultural extension officers in the study area. The results show that access to extension services was negatively related to the uptake of digital solutions that

Table 4
Correlations of solutions derived from the multivariate probit model.

Combinations	Coefficient	Standard error	z	p-value
Market solutions and financial solutions	0.009	0.115	0.070	0.940
Market solutions and access to inputs	0.094	0.056	1.670	0.095
Market solutions and access to extension services	0.344	0.055	6.240	0.000
Financial solutions and access to inputs	−0.021	0.079	−0.260	0.793
Access to extension services and financial solutions	0.031	0.084	0.370	0.715
Access to extension services and access to inputs	0.592	0.047	12.480	0.000

Notes: Coefficients are statistically significant at $p < 0.05$. Positive and negative coefficients represent complementarities and substitutability relationships between digital agricultural solutions, respectively.

enhance access to inputs and extension services. Farmers who received extension visits were 38 % and 75 % less likely to adopt input-related solutions and extension-related digital solutions, respectively. Access to agronomic training positively influenced farmers' decision to adopt digital agricultural solutions. Farmers who received training on good agricultural practices were 65 %, 94 %, and 43 % more likely to adopt market-oriented solutions, input-related solutions, and solutions that enhance access to extension services, respectively. The relatively high demand for digital solutions that enhance access to inputs could be due to the enhanced knowledge that is gained about the importance and appropriate use of improved and approved inputs.

Table 4 presents multivariate probit estimates of the correlations between the different digital agricultural solutions available to farmers in the Bono East Region. It was hypothesized that farmers could use digital solutions as substitutes or as complements. Digital solutions serve as complements when farmers combine them. On the other hand, they serve as substitutes when farmers replace one with the other. The results reveal that farmers who adopted market-related solutions were 9% points more likely to adopt input-related solutions. The results also show that market-oriented digital solutions and digital solutions that enhance access to agricultural extension services were complements. Categorically, farmers who adopted market-oriented digital agricultural solutions were 34% points more likely to adopt digital agricultural solutions that promote access to agricultural extension services. Farmers complemented digital agricultural solutions that enhance access to extension services with solutions that enhance access to agricultural inputs. This is intuitive as access to extension service is required to understand how to appropriately use inputs. Farmers who adopted extension-related solutions were 57 % more likely to adopt solutions that improved access to inputs.

4.3. Factors influencing the intensity of adoption of digital agricultural solutions

The study used a Heckpoisson model to analyze the factors that influence the intensity of adoption of different digital agricultural solutions among farmers in the Bono East region. The results are presented in Table 5. The results reveal that socio-demographic factors, farm characteristics, and institutional factors influence the intensity of digital agricultural solutions adopted by farmers. Migratory status negatively influences the likelihood of adoption and intensity of adoption of digital agricultural solutions. This means that migrant farmers are less likely to adopt digital agricultural solutions. Even when they adopt, they are likely to adopt fewer digital agricultural solutions. Whereas the variable, gender, did not matter for the decision to adopt digital agricultural solutions, it negatively influenced the intensity of adoption of digital agricultural solutions. This means that female farmers are more likely to adopt more digital agriculture solutions.

Wages paid by farmers were found to positively influence the intensity of the adoption of digital agricultural solutions. This implies that farmers who pay higher wages to workers are more likely to increase the adoption of different digital agriculture solutions. The results show that farm income positively influences the probability of adoption and the intensity of adoption of digital agricultural solutions. This means that an increase in the income of farmers is likely to increase the number of digital agricultural solutions a farmer adopts.

The study results show that farm size negatively influenced the propensity of adoption and the intensity of adoption of digital agricultural solutions. This implies that having a larger farm reduces the propensity to adopt digital agricultural solutions and the number of digital agricultural solutions. Furthermore, access to a working radio by farmers increases their likelihood of adopting digital agricultural solutions.

The results also show that institutional factors such as group membership, access to extension services, and training influenced the likelihood and intensity of the adoption of digital agricultural solutions. Group membership was used as an exclusion restriction since the solutions were introduced to farmers as a group. Accordingly, farmers who belonged to groups had a higher propensity to adopt digital agricultural solutions. In addition, the study results indicate that the more farmers receive training services, the more likely they

Table 5
Drivers of adoption and intensity of adoption: Heckpoisson model.

	Selection equation			Intensity equation		
Variables	Coeff	Std. Err.	P > z	Coeff	Std. Err.	P > z
lnwages	−0.0002	0.0001	0.159	0.00004***	0.00001	0.006
Migratory Status (Migrant)	−0.456***	0.153	0.003	−0.275***	0.042	0.000
lnschoolingyears	0.044	0.069	0.523	0.044	0.069	0.523
lnfarmsize	−0.030***	0.011	0.005	−0.010***	0.003	0.003
Gender (Male)	−0.136	0.146	0.352	−0.072*	0.043	0.093
lnincome	0.504***	0.171	0.003	0.286***	0.039	0.000
Group membership (Yes)	1.703***	0.219	0.000			
Extension access (Yes)	−0.173	0.162	0.284	−0.327***	0.046	0.000
Training (Yes)	1.651***	0.200	0.000			
Have Radio	1.418***	0.225	0.000	−0.060	0.049	0.227
Constant	−3.840***	1.213	0.002	−0.799***	0.292	0.006
athrho	1.642***	0.582	0.005			
lnsigma	−4.231***	1.243	0.001			
rho	0.928	0.081				
sigma	0.015	0.018				
Wald test of indep. eqns. (rho = 0): chi2 (1) = 7.97 Prob > chi2 = 0.0047						

Note: * and *** represent statistical significance at 10 % and 1 % levels, respectively.

will adopt digital agricultural solutions. The results further show that farmers who were visited by agricultural extension officers were less likely to adopt These visits also reduced the number of solutions adopted by farmers in the region. This implies that the more extension visits farmers receive, the less likely it is for them to adopt digital agriculture solutions.

Table 5 shows the results of the Heckpoisson model on the drivers of digital agriculture solutions and the intensity of the adoption.

5. Discussion

Digital agricultural solutions are crucial in enhancing agricultural productivity and market efficiency. The study found that farmers adopted four main groups of digital agricultural solutions. These include market-oriented solutions, digital financial solutions, and solutions that enhance access to inputs and extension services. Market-oriented solutions were the most adopted solutions followed by solutions that enhanced access to extension services and inputs. Whereas the adoption of market-oriented solutions was relatively high, the adoption of solutions that promoted access to extension services and inputs was relatively low. Similarly, finance-related solutions were the lowest. The low adoption of these technologies could be attributed to their low penetration rate on one hand or the low demand for these services. According to Missiame et al. [42], farmers preferred to borrow from informal sources rather than formal sources. This could account for the low rate of adoption of finance-oriented solutions. Peperah et al. [43] confirm that the use of mobile money among Ghanaian farmers is relatively low (28 %). This emphasizes the need for financial technology (Fintech) firms to expand their operations to rural households. Further, the study revealed significant gender gaps regarding the use of agricultural solutions that enhanced access to market and extension services. Specifically, the use of these services or technologies was male-dominated.

The results from the study show that several factors (sociodemographic characteristics, farm characteristics, and institutional factors) influence farmers' decisions to adopt digital agricultural solutions. This confirms the studies by Sohail et al. [40], Workie et al. (2023) [23], Vecchio (2020) [25], and Akudugu et al. [46] who argue that sociodemographic variables such as age, income, and marital status are crucial drivers of farmers' adoption behaviour regarding improved agricultural innovations. These factors have been found in this study to play a significant role in understanding the adoption of digital agricultural solutions. The study revealed that older farmers are less likely to adopt digital agricultural solutions while younger farmers are more likely to adopt digital agriculture solutions. This finding is consistent with Bukchin [44]and Mukasa [45]who concluded in their study that young farmers are more aware and ready to adopt new technologies in farming for long-term benefits than older farmers. This means that creativity from stakeholders such as Agritechs may encourage older farmers to be open to adopting digital agricultural solutions. It also implies that complementing digital agricultural solutions with capacity development can accelerate their adoption. These findings also confirm Roger's theory of technological diffusion which posits that sociodemographic factors such are age and marital status can influence the adoption of an innovation [22].

Our study revealed that the adoption of digital agricultural solutions by farmers is greatly influenced by the wages paid to farm workers such that farmers who paid higher adopted different digital agricultural solutions. This is perhaps because such farmers are wealthy and can afford to invest both in labour and technology for higher yields. This finding is similar to Bukchin and Kerret [44] and Akudugu et al. [46], who found that the adoption of agricultural technology is dependent on the endowment of the farmer since they can adopt technology faster than poor farmers. Farmers who pay higher wages have a higher propensity to invest in agricultural production, hence the study revealed that they had a higher propensity to adopt different digital agricultural solutions to increase farm productivity.

Consistent with the findings of Hu et al. [47] and Brown et al. [48], we found that farmers with larger farm sizes were more likely to adopt financial-oriented solutions whereas farmers with smaller farm sizes were more likely to adopt digital agricultural solutions that enhanced access to inputs and extension services. This is intuitive given that large-scale farmers are more likely to have access to inputs and receive frequent extension visits compared to smallholder farmers. Accordingly, smallholder farmers have a higher tendency to pursue solutions that could enhance their access to inputs and extension services. The magnitude of the effects shows that financial solutions are very important to farmers with larger farmers whereas smallholder farmers have a higher need for extension service compared with inputs. Discussing this issue further, their relatively low need for inputs-oriented solutions implies that smallholder farmers do not have an urgent need for mechanized inputs compared with their needs for agronomic training. Given that most of the agricultural solutions are in the trial stages and trials are more likely to be conducted on small farms, farmers with smaller land sizes had a higher tendency to be exposed to these multiple solutions, thereby increasing the number of solutions adopted. This is however contrary to the findings of Tamirat et al. [49], and Castle et al. [50]who argued that large-scale farmers would take advantage of economies of scale and are more likely to afford the investment of several new technologies.

The study further showed that access to credit enables farmers to adopt digital agricultural solutions. This finding agrees with the studies conducted by Ref. [39] who found that access to agricultural credit enables farmers to overcome financial problems associated with the adoption of digital agricultural solutions as compared to farmers who do not have access to credit. The results further show that making credit more accessible to farmers intensifies their adoption of digital agricultural solutions since they become resource-endowed and can afford multiple solutions to enhance farm productivity. Further, farmers who access agricultural credit from financial institutions are more ready to invest in farming activities which increases their tendency of adopting multiple solutions. We found that those who could not access credit from financial institutions were more likely to pursue digital financial solutions. Those who accessed credit from financial institutions, on the other hand, were less likely to pursue digital financial solutions. Instead, these farmers had a very high need for market-oriented solutions as well as solutions that intensified their access to inputs and extension services. Their increased demand for inputs and extension services could be tied to their acquired ability to afford them.

Farmer group membership was found to influence farmers' decision to adopt different digital agricultural solutions and the rate of the adoption of these solutions. This finding was realized in the study of Quaye et al. [51] where farmer-based organizations have been found as important channels for the dissemination of technology for farmers. In the study area, the farmers are organized in groups by the digital agricultural solutions providers, after which the technologies are introduced to these farmers in groups. Also, the introduction of digital agricultural solutions for farmers is sometimes organized by non-governmental organizations in groups. Membership in farmer-based organizations increases the propensity of benefiting from such projects which increases farmers' tendency to adopt multiple digital agricultural solutions. Categorically, the results show that farmers who participated in groups adopted different digital agricultural solutions. This is however contrary to the findings of Ahmed and Anang [32] who found that group membership is associated with lower adoption of improved agricultural technology.

Based on our findings, the farmers' decision to adopt a digital agricultural solution is influenced by the provision of agronomic training to the farmers. This finding is similar to the study of Liu et al. [52] who argued that participation in technical training can significantly enhance the probability of the adoption of agricultural technology. Access to extension services was found to reduce the adoption of digital agricultural solutions. This implies that farmers who had been visited by agricultural extension officers did not see the need to adopt digital agricultural solutions since some services provided by extension officers were sufficient for them to increase output. This finding is contrary to the finding of Danso-Abbeam [53] who found that extension services increase the adoption of soil and water conservation practices in the northern region. Similarly, according to Xu et al. [54], the number of extension contacts a farmer receives plays a significant role in promoting the adoption of agricultural technology. The finding from the study therefore implies that digital agricultural solutions should be enhanced in areas where access to extension officers is limited. On the other hand, farmers who participated in agronomic training and other capacity development programmes were more likely to adopt digital agricultural solutions and even at an increased rate. This means that capacity-building training for farmers should be enhanced to intensify the rate of adoption of digital agriculture solutions.

The study acknowledges some limitations that could affect the findings in the study. These limitations include not capturing qualitative data that could provide in-depth details to unravel some of the reasons for the adoption of digital agriculture solutions. Furthermore, the cross-sectional nature of the data collected cannot be used to analyze the behaviour of farmers concerning the adoption of digital agriculture over some time. Also given the differences in agro-ecological zones in Ghana, the findings of the study might not be applicable in other regions. Further, an analysis of the impact of the adoption of digital agricultural solutions might provide more insights into the urgency of the issue. This study did not consider the impacts of digital agricultural solutions on farm households. In addition, other variables such as complexity and trialability of the innovation as put forward by Roger's theory of diffusion were not considered in this study and could also influence the adoption of digital agriculture by smallholder farmers. Geographically the study is limited to only six districts and its findings might not be applicable in the remaining districts and some other parts of the country. This is because some variables (sociodemographic) used to understand the adoption of digital agriculture in the study area might vary in other places. Despite these limitations, the study is still relevant and its findings provide a step toward understanding the factors that influence farmers in the adoption of digital agriculture solutions in Ghana and how intense this adoption is.

6. Conclusion and policy implications

The study analyzed the factors that influence the adoption of digital agricultural solutions by smallholder farmers in the Bono East region with a sample of 1199. The multivariate probit model and the Heckpoisson regression model were used to analyze the adoption of digital agricultural solutions by smallholder farmers in the study area. The study concludes that the adoption of digital agricultural solutions by smallholder farmers is influenced by sociodemographic factors such as age, gender, income, and marital status and institutional factors such as access to credit, access to extension services, participation in agronomic training and membership in farmer-based organizations. The policy implication is that agricultural technology companies should consider these socio-demographic factors in developing, managing, and deploying digital agricultural solutions to farmers.

Given that farmers' access to credit is likely to influence their decision to adopt digital agricultural solutions, government and development partners should increase budget allocation to the agricultural sector and develop policies such as lowering interest rates that will encourage farmers to access credit facilities. Additionally, financial institutions should supply agricultural credit facilities to small-scale farmers at low-interest rates and better terms of conditions. Also, national flagship programmes such as the Planting for Food and Jobs project of Ghana should integrate capacity-building activities targeted at enhancing farmers' knowledge of digital agricultural solutions. This will equip farmers with the knowledge and skills required to adopt digital agricultural technologies. Since farmers' group membership and access to extension services also affect their decisions to adopt digital agricultural solutions, the Government of Ghana and development partners should encourage farmers' organizing and facilitate them into co-operatives to give them a legal identity to intensify their collective voices in policy engagement with digital agricultural companies. Since reduced access to extension visits increases a farmer's propensity to adopt digital agricultural services, government and development partners should invest in intensifying the volume and frequency of extension services that are channeled through digital platforms to farmers, especially farmers in remote areas who receive little or no extension visits.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Licarion Kunwedomo Miine: Methodology, Formal analysis, Data curation, Conceptualization, Resources, Writing - original draft, Writing - review & editing. **Angela Dziedzom Akorsu:** Supervision, Conceptualization, Methodology, Writing - review & editing. **Owusu Boampong:** Supervision, Conceptualization, Methodology, Writing - review & editing. **Shaibu Bukari:** Supervision, Conceptualization, Methodology, Writing - review & editing.

Declaration of competing interest

We are pleased to declare that there is no conflict of interest in relation to our manuscript entitled ***Drivers and intensity of adoption of digital agricultural services by smallholder farmers in Ghana***.

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