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Technology adoption behaviors of farmers during crises: What are the key factors to consider?

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ABSTRACT

The Covid-19 pandemic required economic agents, in this case farmers, to make immediate decisions with an eye on a future characterized by high level of uncertainty. Using a multivariate probit, this paper examines the factors that farmers, as economic agents, considered at the peak of the pandemic in their digital (e-service) technology adoption decisions. The results indicate that the key factors that influence digital technology adoption behaviors of farmers are age, gender, education, level of dependency, experience in farming, access to credit and perceived possible impact of the pandemic on production activities. These factors were found to have different levels of influences on the adoption of different digital technologies that could help reduce physical contacts in line with nationally determined Covid-19 protocols whiles sustaining agricultural production activities. Digital technologies that facilitate easy access to good agronomic practices, weather information services, input and output market information services and financial services were identified as crucial. The general conclusion of this paper is that farmers are willing to adopt technologies that add value to their welfare through timely resolution of problems that confront them. Thus, value propositions – such as relevance, effectiveness, efficiency, sustainability, and impact – must be the key considerations in policy interventions that promote positive technology adoption behaviors.

1. Introduction

The Covid-19 pandemic created dire consequences across the world. The pandemic threatened to reverse years of gains made in the socio-economic arena with serious disruptions to livelihoods. The situation was exacerbated by the lockdowns and restrictions on free movements to contain the spread of the disease [1]. The containment policies resulted in disruption of supply chains, especially the agri-food systems [2,3]. The socioeconomic costs of the containment measures adopted by national governments across the world include increased poverty, food insecurity and malnutrition with long-term consequences on the human capital base for sustainable and inclusive development [4–7]. This required economic agents, particularly farmers, to make immediate decisions with an eye on a future characterized by high level of uncertainty. This included decisions to minimize the adverse effects of supply-side shocks on agricultural commodity value chains [8]. The situation is worse in the developing world where the pandemic has resulted in about 115 million additional people being extremely poor [9]. The impact of the Covid-19 pandemic on food systems is one of the major priorities of scholars and policymakers [2,5,10].

In recent times, there have been reports of soaring food prices across the world with serious negative implications for food and nutrition security. The hikes in food prices will most likely result in social unrest, political upheavals, malnutrition and increased poverty among others [11–15]. The situation has been made worse by the Russia-Ukraine War, which is happening at a time that the world is struggling to cope with the devastating impacts of the aftermath of the global pandemic. In their study of the effects of Covid-19 containment measures implemented by China, particularly countrywide lockdown, on food prices, Ruan et al. [16] report that it led to increases in food, particularly vegetable, prices.

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Similarly, a study by Akter [17] report that physical restrictions such as stay-at-home led to increased food prices in 31 countries in Europe.

It has been reported in the empirical literature that the Covid-19 global pandemic led to reduction in agricultural production. This is because the restrictions on movements disrupted agricultural commodity supply/value chains thereby distorting labor supply and input distributions [18–22]. For example, using panel data to analyze effects of the pandemic on food production in Bangladesh, Gatto and Islam [23] report that Covid-19 caused reduction in agricultural production, reduction in the share of output sold, reduced dietary diversity and expenditure on education. Lockdowns imposed at the peak of the pandemic resulted in significantly reduced labor market participation leading to increased food insecurity in Nigeria [5]. Similarly, it has been reported that households which experienced Covid-19 induced income shocks suffered increased food insecurity [24]. This is largely attributable to limited access to input and output markets, which inherently leads to increases in prices of goods and services [25]. The restrictions in movements meant loss of jobs for many people, especially the poor and vulnerable in areas with limited employment opportunities as well as business failures due to limited market access [2].

In Kenya, Covid-19 related disruptions in transportation of goods and services were reported to have led to delays in food supplies, with serious consequences on food and nutrition security of the poor and vulnerable [26]. The closures also affected informal markets in many areas disrupting the supply of agri-food products to households, particularly those poor households that depend on such markets for fresh farm produce such as fruits, vegetables, meat and eggs [27]. Issues of shortages of labor to perform critical functions in informal markets, especially the food processing industry, further exacerbate the impacts of the pandemic on livelihoods [27].

The pandemic caused huge job losses with women being the worse affected. This resulted in reduction in food consumption ultimately impacting food and nutrition security negatively. This assertion is consistent with the findings of Dang and Nguyen [28] that the pandemic caused more job and income losses that affected women more than men. Evidence also shows that female-headed households had a higher probability of experiencing food insecurity than those headed by males [29]. Most importantly, the lockdown measures limited access to agricultural extension and advisory services by farmers [27]. This is particularly so with the in-person extension services delivery to farmers. This means farmers needed to adopt measures to mitigate the negative impacts of the pandemic on their production. According to Paganini et al. [30], some of the mitigation measures adopted to deal with the negative effects of the pandemic include vegetable production, reduction in spending, and change of diets among others. In their study, Tripathi et al. [31] report that farmers in South Africa relied on family labor to offset the high labor cost induced by the pandemic, consumed what they produced, reduced farm sizes as well as sold off household assets such as livestock to cope. Same authors report that Tanzanian farmers traded among themselves to remain viable. What seems to have helped build the adaptive capacity of people in the pandemic situation is the availability of smartphones with multiple functions [32]. Digital agricultural technologies are assuming central importance in recent times, and especially during periods of crises like the Covid-19 pandemic. For example, FAO [33] and Roshetko et al. [34] note that digital services (such as extension, financial, marketing and weather/climate) for farmers are key innovative technologies for the future.

Smallholder farmers faced several barriers to the adoption and use of digital technologies prior to the Covid-19 pandemic. Some of these are a lack of digital infrastructure in farming areas [35,36], problems with electricity infrastructure for the dissemination of agricultural information in rural areas, and socio-economic factors such as low education, poverty and scarcity of relevant content in local languages [35]. However, evidence points to the Covid-19 pandemic inducing a phenomenal increase in the use of e-commerce and other e-services in several developing countries [37]. For example, the rise in the use of e-services between 2019 and 2020 in several developing countries was in double digits [38,39]. This presents a picture of Covid-19 inducing a behavior change in favor of the adoption and use of e-services technology, which already existed prior to the pandemic, and thus forms the subject of investigation in this study.

However, what is lacking in the empirical literature is the type of technologies, particularly digital technologies, adopted during the pandemic for improved food production. For instance, to what extent did farmers make use of e-extension services, e-input/output market information services, e-payment services, and e-weather information services (or generally, digital services/e-services) to offset Covid-19 induced production challenges? Thus, this paper examines the technology adoption behaviors of farmers during the pandemic. This provides a critical input into policy and practice in the agricultural sector for improved agricultural production and livelihoods development. The rest of the paper is organized into three (3) main sections – the materials and methods; results and discussion; and conclusion and implication for policy.

2. Institutional voids and technology adoption by smallholder farmers: theoretical perspectives

Institutional voids, in the context of operations of smallholder farmers, refer to the absence or failure or deficiencies in formal or informal institutions [40], such as rules and regulations, infrastructure, specialized intermediaries, and support systems – like mechanism for contract enforcement, property rights, and governance structure – [41], which can impede the adoption and effective use of agricultural technologies. This is so because the presence of such voids will greatly hinder the efficient functioning of the institutions required for the development of such technologies [42]. As such, their presence affects the choices and actions of smallholder farmers.

The concept of institutional voids is observed to be widely studied in business management in the context of developing countries [40] as these countries lack well-functioning institutions and are mostly resource constrained. Against this backdrop, smallholder farmers are affected by the institutional voids, and they respond to these by adopting various strategies including use of substitute mechanisms such as networking [43], or social connections [44] or trust [45]. In using these substitute mechanisms, smallholder farmers in developing countries may evolve innovative means of navigating the voids in the face of acute resource constraints. For example, social entrepreneurship is used in environments where serious cultural, environmental and socio-economic issues exist [40,46], and frugal entrepreneurship is employed in environments where there are significant resource constraints [47]. While social entrepreneurship generates societal benefits or reduces societal costs, i.e., creates social value, and ensuring financial sustainability at the same time [48], frugal entrepreneurship is a type of entrepreneurship which brings a cost-effective innovation to the market utilizing limited resources in an environment that is extremely constrained [47]. Other specific approaches are *bricolage* in which individuals rely extensively on experience and observation to overcome their constraints, and *ingenieuring* in which problems are addressed beginning with abstract concepts rather than practical experience [42, 49].

Even though the concept of institutional voids has been very well studied in the context of business management in developing country contexts [40], it has been less explored in the context of technology adoption in agriculture, but where it exists it has not been very direct and explicit. Some theoretical perspectives can be inferred to have been explored in institutional voids in technology adoption in agriculture and are: First, institutional theory [50], which emphasizes the influence of institutional factors on technology adoption by farmers. Within this framework, institutional voids can create uncertainties, lack of trust, and inadequate support mechanisms, making it challenging for farmers to adopt and integrate new technologies. Second, the innovation diffusion theory, which examines the process by which innovations are adopted and spread within a social system [51]. Within this lens, institutional voids may hinder the diffusion process of technology by creating barriers to information flow thereby limiting access of farmers to knowledge about new technologies. Next, is the social capital theory, which tends to highlight the role of social networks, relationships, and trust in facilitating technology adoption [52]. The presence of institutional voids may impede social capital effect by dwindling the chances for collaboration and knowledge sharing among farmers, which can in turn hinder the adoption and use of new technologies. Finally, the perspective of the resource-based theory or view focusing on the role of (tangible or intangible) assets or resources, capabilities, and constraints in influencing technology adoption has also been explored [53]. Institutional voids can lead to resource constraints (such as limited access to credit, land, or infrastructure) for farmers, which will make it difficult for them to invest in the adoption of new technologies.

The foregoing perspectives are relevant to the current study, which emphasizes smallholder farmer behavior change during pandemics in a typically resource-constrained developing country context (i.e., Ghana), and how that affects their ability to overcome their challenges in the adoption and use of technology in those circumstances. This is also a unique feature of the current study since the limited previous studies about institutional voids and technology adoption focused generally on agriculture or commercial farmers as opposed to smallholder farmers in developing countries.

3. Materials and methods

3.1. The study site

The study was conducted in five (5) of the sixteen (16) regions of Ghana. All the selected regions were from the northern savannah and part of the transition agro-ecological zones. Specifically, the studied regions were the Upper West, Upper East, North East, Northern, and Bono East regions. The study regions are shown in Fig. 1. Except the Bono East Region, the rest have unimodal rainfall with the rainy season spanning May to October.

3.2. Sampling and data management

The study communities and respondents were sampled using multi-stage (four-stage) sampling strategy. The first stage was stratification of the selected regions into districts, from which 22 Districts (6 in Upper West Region; 7 in Upper East Region; 3 in North East Region; 4 in Northern Region; and 3 in Bono East region) were selected for their relevance. The second stage was a further stratification of the selected districts in accordance with the agricultural operational zones, which constituted the strata. Simple random sampling was then used in the third stage to sample the required number of communities from each stratum. The fourth stage was the use of random sampling again to choose the required number of households in the community for the survey.

In all, 1304 farmers comprising 434 from Upper West, 394 from Upper East, 150 from North East, 200 from Northern and 136 from Bono East regions were interviewed. However, data from 1294 farmers were used for the analyses due to incomplete information. Field data collection was carried out from May to June 2020. A combination of methods was used in the data collection with the administration of semi-structured questionnaire to farmers through face-to-face mode using computer assisted personal interview (CAPI) devices as the main method. Due to the Covid-19 pandemic situation, enumerators were assigned to specific districts throughout the data collection period to

Fig. 1. The study regions.

minimize their movements. Enumerators observed all the Covid-19 protocols including social/physical distancing, wearing of masks, using hand sanitizers, and avoiding handshakes.

Data inputting was done directly by enumerators through the CAPI devices to a server. The submitted data were synchronized/backed-up daily to prevent any loss of data. The data were then cleaned, aggregated, and converted to Excel, SPSS and Stata formats. The survey data were used for the analyses. The analyses were basically undertaken using quantitative techniques to unpack the various factors that influence the decisions of farmers to adopt certain digital agricultural production services. A snapshot of the data used is found in Table 2.

3.3. Analytical framework

The analyses involved using quantitative techniques to unpack the various factors that influence the decisions of farmers to adopt specific digital agricultural production services. Theoretically, this paper is motivated by the theory of behavior modification [54] and the random utility theory developed by McFadden [55]. This is because of the belief that farmers' technology adoption behaviors can be modified by several forces. Some of these forces are gender, age, access to credit, and level of education among others (see, for example [56–58]). Adoption of the digital agricultural production services technologies is thus the result of the forces at play in the psychological field. This means that there is the need to identify such forces in the farmers' technology adoption decision making processes to estimate the chances of success in promoting the specific technologies [59]. Consistent with the random utility theory as well as the threshold decision making theory [60], adoption of new technologies is possible only when the net benefit is greater than zero, which could be mathematically expressed as:

$$K_{ij}^{*} = E[\mathrm{U}(\pi\mathrm{A})] - \mathrm{E}[\mathrm{U}(\pi\mathrm{N})] > 0 \mathrm{or} E[\mathrm{U}(\pi\mathrm{A})] > \mathrm{E}[\mathrm{U}(\pi\mathrm{N})] \tag{1}$$

where $\mathrm{U}(\pi\mathrm{A})$ and $\mathrm{U}(\pi\mathrm{N})$ are respectively benefit or utility derived from adoption and non-adoption of the new technologies.

The net benefit K_{ij}^{*} derived by a farmer from the adoption of *jth* digital agricultural production service technology is a latent variable determined by given factors(X_i).(see Tables 1 and 2) and the error term (ε_i). The model is mathematically specified as:

$$K_{ij}^{*} = X_i^{'}\beta_j + \varepsilon_{ij} \ (j = y_1, y_2, y_3, y_4) \tag{2}$$

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

Table 1
Variables included in the multivariate probit model.

Variable	Means of Measurement	A priori Expectation
Dependent Variables		
e-extension services (y_1)	Dummy (Yes = 1; No = 0)	
e-price information (y_2)	Dummy (Yes = 1; No = 0)	
e-payment services (y_3)	Dummy (Yes = 1; No = 0)	
e-weather information services (y_4)	Dummy (Yes = 1; No = 0)	
Dependent Variables		
Gender (X_1)	Dummy (1 = M; 0 = F)	+
Age (X_2)	Years	+/−
Education (X_3)	Years	+
Household size (X_4)	Number	+
Experience (X_5)	Years	+/−
Farm size (X_6)	Hectares	+
Savings (X_7)	Dummy (1 = Yes; 0 = No)	+
Credit (X_8)	Dummy (1 = Yes; 0 = No)	+
Farm investment (X_9)	GHS	+
COVID-19 Awareness (X_{10})	Dummy (1 = Aware; 0 = Not aware)	+

Source: Field Survey Data, 2020.

Table 2
Descriptions of data on variables in the multivariate probit model (n = 1294).

Variables	Mean	Standard Error	95% Confidence Interval	
e-extension services (y_1)	0.5479	0.0138	0.5208	0.5751
e-price info (y_2)	0.5603	0.0138	0.5332	0.5874
e-payment services (y_3)	0.3833	0.0135	0.3568	0.4098
e-weather info services (y_4)	0.5533	0.0138	0.5262	0.5804
Gender (X_1)	0.9505	0.0060	0.9387	0.9624
Age (X_2)	48.4521	0.3850	47.6967	49.2075
Education (X_3)	6.1136	0.0678	5.9805	6.2467
Household size (X_4)	8.8988	0.2072	8.4922	9.3053
Experience (X_5)	23.6553	0.3694	22.9307	24.3800
Farm size (X_6)	12.9909	0.7755	11.4696	14.5123
Savings (X_7)	0.8022	0.0111	0.7804	0.8239
Credit (X_8)	0.2226	0.0117	0.1996	0.2456
Farm investment (X_9)	861.5765	100.0266	665.3443	1057.8090
Covid-19 Awareness (X_{10})	0.9560	0.0057	0.9448	0.9671

Source: Authors' Estimations, 2022.

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

However, it has been observed that the adoption choice by farm households is multivariate in nature and so the appropriate modelling procedure should not be binary or univariate but must consider the interactions and possible simultaneity of the adoption decisions (see, for example [61–63]). In the light of this and given that there were multiple technologies available to farmers to adopt as a means of coping with the challenges imposed by the pandemic, the analysis here is pursued at the multivariate level to account for possible contemporaneous correlation or correlated disturbances among the models (that is, all four digital agricultural production services technologies, *viz.*, e-extension, e-market information, e-payments, and e-weather information). If the error term in the utility model is assumed to be normally distributed, the analysis can be carried out using a probit model. The multivariate probit framework extends univariate and bivariate models to include three or more outcome variables yielding a system of equations like seemingly unrelated regressions model and it is defined as [64]:

$$y_m^{*} = x_m^{'}\beta_m + e_m, Y_m = 1 \text{ if } y_m^{*} > 0, 0 \text{ otherwise}, m = 1, \ldots, M, \tag{4}$$

with $E[e_m|x_1, \ldots, x_M] = 0$, $Var[e_m|x_1, \ldots, x_M] = 1$, $Cov[e_j, e_m|x_1, \ldots, x_M] = \rho_{jm}$, and $(e_1, \ldots, e_M) \sim N_M[0, R]$. This implies that the error terms are multivariate normally distributed with zero mean and a variance-covariance (or correlation) matrix of R. The joint probabilities that enter the log-likelihood function are given by:

$$\mathrm{Prob}(Y_{i1}, \ldots, Y_{iM}|x_{i1}, \ldots, x_{iM}) = \Phi_{\mathrm{M}}\left(q_{i1}x_{i1}^{'}\beta_1, \ldots, q_{iM}x_{iM}\beta_M, R^{*}\right), \tag{5}$$

where $q_{im} = 2y_{im} - 1$, and $R_{jm}^{*} = q_{ij}q_{im}\rho_{jm}$.

The M-variate integrals involved in the multivariate probit model makes it difficult to estimate and the computation process rather burdensome. As a result, simulation-based techniques are normally used (see, for example [64]).

Empirically, the models of the four (4) digital agricultural production services technologies covered in this study, which are simultaneously estimated using the multivariate probit are specified as:

$$y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon_1 \tag{4}$$

$$y_2 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon_2 \quad (5)$$

$$y_3 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon_3 \quad (6)$$

$$y_4 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10} + \varepsilon_4 \quad (7)$$

The choice of the variables in the models is justified by previous studies as discussed earlier.

4. Results and discussion

In general, majority of the farmers who participated in the study indicated their adoption of e-extension (55%), e-market information on inputs and outputs prices (56%) and e-weather information services (55%) with the minority (38%) saying they were making use of e-payment services through mobile money platforms (Table 2). The descriptive analyses show that majority (95%) of the research participants were male household heads with an average age of 48 years, averagely 6 years of formal schooling depicting an institutional – social – void [40], household sizes of 9 persons, about 24 years of experience in farming and farm sizes of about 13 acres (Table 2). Majority of them also indicated that they make savings for "rainy days" (80%) with only about a fifth (22%) of them indicating they have had access to credit (Table 2). On the average, farmers invested GHS862 (US$154) in their farm production with the majority (96%) of them reporting awareness of the Covid-19 pandemic (Table 2).

The study modelled socioeconomic characteristics of farmers to determine which of them should be the focus of policy in promoting the adoption of digital agricultural production services technologies in the era of global uncertainty. The estimated multivariate probit produced a likelihood ratio test, which is significant at 1% (Table 3). This means that the rho values, which are the correlation coefficients between the residuals of each of the probit models, are statistically significantly different from zero. The implication of this is that the use of the multivariate probit model is appropriate.

The multivariate probit results indicate that the adoption behavior of farmers of e-extension services is significantly influenced by age, level of education, farm size, access to credit, farm investment, and awareness of the Covid-19 pandemic (Table 3). In particular, the results revealed that the probability of adopting e-extension services increases with increasing age, farm size, and access to credit (Table 3). Specifically, every extra year gained by a farmer increases their probability of adopting e-extension services, *ceteris paribus*. This is probably because older farmers are independent and so can make digital technology adoption decisions by themselves. Like Sabastian et al. [65] in Indonesia and Wongnaa et al. [57] in Ghana who found area cultivated to be positively related to adoption of management practices, the results of this study also revealed farm size to have a positive and significant relationship with probability of adopting e-extension services and same applies to access to credit. On the other hand, the higher the level of education, experience in farming and farm investment, the lower the probability of adoption of e-extension services by farmers (Table 3). These findings are contrary to expectations but indicate that farmers in those categories are confident in their own abilities to farm and access information, and thus they do not need to rely on digital extension services. However, the effect of education on the adoption of e-extension is in line with that obtained by Issahaku et al. [66], who reported that additional years of education reduced the likelihood of farmers complying with extension services. More importantly, those farmers who indicated that they were aware of the Covid-19 pandemic and its consequences were more likely to adopt e-extension services delivery than those who were unaware of the disease and its possible consequences on their livelihoods. This is in line with the result obtained by Martey et al. [58] that price shocks occasioned by Covid-19 had positive effect on the adoption of at least half of the number of management practices studied.

The multivariate probit model results also revealed that the factors that significantly influence the adoption of e-market information services (information on inputs and outputs prices) are gender, access to credit and awareness of the Covid-19 pandemic. Gender and access to credit were found to have significantly positive influence on the probability of adoption of e-market information services. The awareness of the Covid-19 pandemic and the potential consequences on livelihoods

Table 3
Multivariate probit results (n = 1294).

Variable	e-Extension	e-Market info	e-Payments	e-Weather info
	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
Gender (X_1)	−0.0004 (0.1678)	0.3050* (0.1581)	−0.0167 (0.1626)	0.0473 (0.1523)
Age (X_2)	0.0058* (.0033)	0.0047 (0.0031)	0.0040 (0.0032)	0.0043 (0.0031)
Education (X_3)	−0.0312** (0.0152)	−0.0094 (0.0147)	−0.0456*** (0.0149)	−0.0020 (0.0146)
Household size (X_4)	0.0017 (0.0053)	−0.0040 (0.0050)	−0.0166*** (0.0053)	−0.0018 (0.0052)
Experience (X_5)	−0.0043 (0.0034)	−0.0043 (0.0033)	0.0013 (0.0034)	−0.0049 (0.0033)
Farm size (X_6)	0.0067*** (0.0020)	0.0019 (0.0012)	0.0032*** (0.0011)	0.005*** (0.0018)
Savings (X_7)	0.0789 (0.0921)	0.0981 (0.0897)	0.1076 (0.0916)	0.1585*(0.0889)
Credit (X_8)	0.2027** (0.0856)	0.1914** (0.0833)	0.1029 (0.0827)	0.1301 (0.0821)
Ln (Investment) (X_9)	−0.0349** (0.0165)	0.0221 (0.0160)	0.0174 (0.0159)	−0.0153 (0.0159)
COVID-19 Aware (X_{10})	0.7692*** (0.1746)	0.6396*** (0.1639)	0.3202* (0.1756)	0.1264 (0.1513)
Constant	−0.6392** (0.2859)	0.1828 (0.2673)	−0.6193** (0.2839)	−0.2477 (0.2605)
Measure	**Coefficient**	**Std. Error**	**z**	**P>|z|**
rho21	0.7563	0.0232	32.60	0.000
rho31	0.6229	0.0304	20.47	0.000
rho41	0.7267	0.0235	30.88	0.000
rho32	0.7398	0.0239	30.90	0.000
rho42	0.8381	0.0162	51.79	0.000
rho43	0.6625	0.0280	23.65	0.000
Goodness of Fit Measures				
Likelihood ratio test of rho21 = rho31 = rho41 = rho32 = rho42 = rho43 = 0: chi2 (6) = 1502.83 Prob > chi2 = 0.0000				

***p < 0.01; **p < 0.05; *p < 0.10.
Source: Authors' Estimations, 2022.

was also found to have a significantly positive influence on the probability of adoption of e-market information services by farmers. Specifically, the probability of adopting e-market information services is higher among men than women (Table 3). The results further indicate that access to credit positively influences farmers' probability of adopting e-market information services, *ceteris paribus*. The positive findings of some of the socio-economic characteristics of the farmer on the adoption of e-market information services is in sync with that of Rahayu and Day [67] who reported positive effects of individual and environmental factors on the adoption of e-commerce by SMEs, in general, in Indonesia. In line with expectation, those farmers who indicated that they were aware of the Covid-19 pandemic and its consequences were more likely to adopt e-market information services than those who were unaware of the disease and its possible consequences on their livelihoods. This finding reflects that reported by Misra et al. [68] to the effect that the Covid-19 pandemic accelerated the adoption of e-market services by small businesses in India.

For e-payments through mobile money applications, the key factors that significantly affect adoption are level of education, household size, farm size and awareness of the Covid-19 pandemic. Contrary to expectation, it was found that level of education had a negative and significant effect on the probability of adopting e-payment services through mobile money platforms. This means that the higher the level of education of a farmer, the lower the probability of adopting e-payment services, *ceteris paribus*. This is probably because more educated farmers already have access to e-payment platforms and so are less likely to want to adopt e-payment services. This result contrasts with the positive effect of education on mobile money technology adoption reported by some studies in other developing country contexts [69,70]. Household size was also found to negatively and significantly, influence farmers' probability of adopting e-payment services (Table 3). This means farmers with large household sizes are less likely to adopt e-payment services to off-set the challenges imposed by restrictions on physical movements during the peak of the pandemic. Farm size was found to have significant and positive influence on the probability of adopting e-payment services as reported also by Abdul-Rahaman and Abdulai [71] for rice farmers in Ghana, implying that farmers who have large farm sizes are more likely to adopt e-payment services than those with small farm sizes. Specifically, a unit increase in acreage under cultivation leads to a corresponding increase in the probability of adopting e-payment services. This is likely a risk management strategy where because they operate large farms, they frequently pay for services and so avoid a situation of having to physically carry cash. It was further found that farmers who were aware of Covid-19 and its consequences had higher probability of adopting e-payment services than their counterparts who were unaware of the disease and its potential impacts on their livelihoods.

The adoption of e-weather information services was found to be significantly influenced by farm size and household savings only. Specifically, it was found that a unit increase in farm size significantly increases the probability of adopting e-weather information services by farmers. Similarly, having household savings was found to have positive significant influence on the probability of adoption of e-weather information services by farmers (Table 3). Generally, the e-weather information is delivered to farmers through mobile phone-based platforms and since the farmers' level of education is very low (an average of only 6 years of formal education), the mode of delivery or communication might be important [72]. For example, an sms-based delivery mode might not be very useful as a lot of them will not be able to read. Sarku et al. [73] note that even though the provision of weather and related information services is increasingly becoming important for smallholder farmers in the context of developing countries to manage the risks associated with climate change and variability, there are gaps between what providers perceive as useful and what users consider as useable information thereby leading to underutilization of weather and other related information services in the farming sector. Other factors that lead to underutilization of weather and climate services are a lack of understanding, unavailable, unsuitable or unusable data [74], low levels of accuracy, forecast parameters that do not meet the decision-makers' needs, inadequate knowledge on the forecasts, inadequate knowledge on climate variability impacts and associated decision responses, skepticism about the scientific credibility of forecasting, among others [75].

A key finding emerging from this study is that the factors that influence the adoption of digital technologies/services (i.e., age, gender, education, household size, farm size, savings, access to credit and investment) in this study are similar to factors that influence the adoption of agricultural management technologies as shown by Akudugu et al. [56], Kallio et al. [76], Sabastian et al. [65], Wongnaa et al. [57] and Martey et al. [58]. Attempts to bolster the use of the digital technologies in agriculture might therefore not present a huge cost outlay since ongoing efforts at promoting management practices will already have some complementary effects. Also, the factors identified here can be related to those identified by Yadav et al. [77] as relative advantage, trialability, compatibility, observability, complexity, aversion to change, technological anxiety, personal and social values. Indeed, the use of the e-services by farmers as covered by this study depends so much on personal and social characteristics, benefits derived, their disposition towards technology, and how easy they can be used. Further, credit stands out as a facilitator of the adoption and use of the digital services, yet smallholder farmers are credit-constrained and so mostly adopt substitute mechanisms such as their own savings and/or investments or that of their close social network [44] as a way of overcoming this void.

The implication of the findings is that policies to promote digital technologies or e-services (i.e., e-extension, e-market information, e-payments and e-weather/climate) to smallholder farmers must take into consideration the age, gender, level of education, household size, farm size, access to credit, savings, farm investment and the Covid-19 awareness or other pandemics and its/their potential impacts on livelihoods. Simelton and McCampbell [78] opine that for e-climate services to be effective, their design should include input from farmers, extension personnel, and policymakers. In a similar vein, Chiputwa et al. [79] noted that to ensure desirable uptake and use among farmers in informing farm management responses for better adaptation to climate change, inclusive and participatory approaches in the provision of general digital technologies in farming should be used. In other words, for optimal outcome in the adoption and use of e-services by farmers, such services should be developed with the farmers not for them. Several other policy-relevant implications are revealed by this study. Firstly, the Ministry of Food and Agriculture, and the Ministry of Trade and Industry, in collaboration with other key stakeholders in the agricultural sector, must take advantage of the opportunities created by the pandemic to respectively sustain the high adoption of e-extension services and the e-market information services among farmers. Secondly, the Bank of Ghana and telecommunication companies must devise strategies to sustain the increased probability of adoption of e-payment services via mobile money platforms. This means that policies, such as the e-levy introduced by the government of Ghana in May of 2022 [80], that impede the use of e-payment system might have to be reconsidered if the increase in probability of adoption of e-payment services caused by the pandemic is to be sustained. Indeed, an assessment of the e-levy has revealed that transactions have reduced drastically with devasting effects on financial inclusion of the vulnerable and government's tax revenue [81]. Thirdly, the pandemic made no significant contribution to the adoption of e-weather information services, and this could be because many farmers rely on indigenous knowledge to predict weather events – a kind of social entrepreneurship or more specifically *bricolage* [42,49] to navigate the lack of trust in weather information services. This is not as good in this era of smart agriculture in response to climate change. Thus, the Ghana Meteorological Agency, in collaboration with the Ministry of Food and Agriculture, should devise policy options that seek to promote the adoption of e-weather information services as this is critical for smart farming in this technological age. As already noted, an effective way of increasing farmers' use of e-climate services is to adopt inclusive and participatory approaches in their design [78,79].

5. Conclusions and policy implications

The Covid-19 pandemic came along with huge challenges and disruptions in economic systems that have over the years been relied upon to support livelihoods. The major productive sectors of economies of all countries in the world experienced unprecedented challenges that kept livelihoods in jeopardy. This is particularly so in the agri-food sector that experienced monumental challenges resulting in historical weakening of food supply chains, putting millions in need of food aid. To be better prepared to handle future pandemics of the scale of Covid-19 and the accompanying economic crises across the world, it is important to understand how economic agents, in this case farmers, make production related decisions in these challenging times with an eye on a future characterized by high level of uncertainty. This is particularly important given that restrictions on physical movements meant that farmers needed to devise alternative ways of accessing the needed services and inputs for food production to continue. Thus, we conclude that indeed, at the peak of the pandemic, farmers relied on e-extension services, e-market information services, e-payment services using mobile money platforms created by telecommunication companies and e-weather information services. Except e-weather information services, the Covid-19 pandemic made significant contributions to the probability of adopting the digital agricultural production services or technologies. In particular, the pandemic increased the probability of adopting e-extension, e-market information and e-payment services. Surprisingly, education had a negative influence on the adoption of e-services. However, farm size, access to credit, and Covid-19 awareness had positive influences on e-service adoption. Each of those four factors were found to influence the adoption of at least two of the four e-services.

The findings of the study have several implications for policy. First, the findings imply that to enhance uptake of digital technologies or e-services by farmers, policy must consider the significant factors including Covid-19 awareness or other pandemics and their potential impacts on livelihoods. Second, an important finding from this study is that the factors that influence the adoption of digital technologies/services in this study are similar to factors that influence the adoption of agricultural management technologies, and this needs to be noted by policymakers. Further, for optimal outcome in the adoption and use of e-services by farmers, such services should be developed with the farmers not for them. Additionally, relevant ministries such as the Ministry of Food and Agriculture, and the Ministry of Trade and Industry should take advantage of the opportunities created by the pandemic to sustain the high adoption of e-extension services and the e-market information services among farmers. Finally, the monetary authority and telecommunication companies will need to evolve ways to sustain the increased probability of adoption of e-payment services via mobile money platforms, including making suggestions to government to reconsider the e-levy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

[1] L. Wang, J. Wang, C. Fang, Assessing the impact of lockdown on atmospheric ozone pollution amid the first half of 2020 in Shenyang, China, Int. J. Environ. Res. Publ. Health 17 (2020) 9004, https://doi.org/10.3390/ijerph17239004.
[2] C.B. Barrett, Actions now can curb food systems fallout from COVID-19, Nature Food 1 (2020) 319–320, https://doi.org/10.1038/s43016-020-0085-y.
[3] C. Elleby, I.P. Domínguez, M. Adenauer, G. Genovese, Impacts of the COVID-19 pandemic on the global agricultural markets, Environ. Resour. Econ. 76 (2020) 1067–1079, https://doi.org/10.1007/s10640-020-00473-6.
[4] C.Y.C. Chen, E. Byrne, T. Vélez, Impact of the 2020 pandemic of COVID-19 on families with school-aged children in the United States: roles of income level and race, J. Fam. Issues 43 (2022) 719–740, https://doi.org/10.1177/0192513X21994153.
[5] M. Amare, K.A. Abay, L. Tiberti, J. Chamberlin, COVID-19 and food security: panel data evidence from Nigeria, Food Pol. 101 (2021), 102099, https://doi.org/10.1016/j.foodpol.2021.102099.
[6] M.K. Kansiime, J.A. Tambo, I. Mugambi, M. Bundi, A. Kara, C. Owuor, COVID-19 implications on household income and food security in Kenya and Uganda: findings from a rapid assessment, World Dev. 137 (2021), 105199, https://doi.org/10.1016/j.worlddev.2020.105199.
[7] A. Ayanlade, M. Radeny, COVID-19 and food security in Sub-Saharan Africa: implications of lockdown during agricultural planting seasons, npj Sci. Food 4 (2020) 1–6, https://doi.org/10.1038/s41538-020-00073-0.
[8] D.A. Sumner, Impact of COVID-19 and the lockdowns on labor-intensive produce markets, with implication for hired farm labor, Choice 36 (2021) 1–11. https://www.jstor.org/stable/27098609.
[9] World Bank, COVID-19 to add as many as 150 million extreme poor by 2021, Press Release, 2020. https://www.worldbank.org/en/news/press-release/2020/10/07/Covid-19-to-add-as-many-as-150-million-extreme-poor-by-2021. (Accessed 17 October 2022).
[10] C. Arndt, R. Davies, S. Gabriel, L. Harris, K. Makrelov, S. Robinson, L. Anderson, Covid-19 lockdowns, income distribution, and food security: an analysis for South Africa, Global Food Secur. 26 (2020), 100410, https://doi.org/10.1016/j.gfs.2020.100410.
[11] D. Headey, S. Fan, Anatomy of a crisis: the causes and consequences of surging food prices, Agric. Econ. 39 (2008) 375–391. https://doi/abs/10.1111/j.1574-0862.2008.00345.x.
[12] C. Hadley, E.G.J. Stevenson, Y. Tadesse, T. Belachew, Rapidly rising food prices and the experience of food insecurity in urban Ethiopia: impacts on health and well-being, Soc. Sci. Med. 75 (2012) 2412–2419, https://doi.org/10.1016/j.socscimed.2012.09.018.
[13] F.H. Ferreira, A. Fruttero, P.G. Leite, L.R. Lucchetti, Rising food prices and household welfare: evidence from Brazil in 2008, J. Agric. Econ. 64 (2013) 151–176. https://doi/abs/10.1111/j.1477-9552.2012.00347.x.
[14] M.F. Bellemare, Rising food prices, food price volatility, and social unrest, Am. J. Agric. Econ. 97 (2015) 1–21. https://www.jstor.org/stable/24476998.
[15] M. Ravallion, Could pandemic lead to famine?. https://www.project-syndicate.org/commentary/Covid19-lockdowns-threaten-famine-in-poor-countries-by-martin-ravallion-2020-04, 2020. (Accessed 16 October 2022).
[16] J. Ruan, Q. Cai, S. Jin, Impact of COVID-19 and nationwide lockdowns on vegetable prices: evidence from wholesale markets in China, Am. J. Agric. Econ. 103 (2021) 1574–1594. https://doi/abs/10.1111/ajae.12211.
[17] S. Akter, The impact of COVID-19 related 'stay-at-home' restrictions on food prices in Europe: findings from a preliminary analysis, Food Secur. 12 (2020) 719–725, https://doi.org/10.1007/s12571-020-01082-3.
[18] D. Laborde, W. Martin, J. Swinnen, R. Vos, COVID-19 risks to global food security, Science 369 (2020) 500–502, https://doi.org/10.1126/science.abc4765.
[19] M.R. Karim, M.T. Islam, B. Talukder, COVID-19′s impacts on migrant workers from Bangladesh: in search of policy intervention, World Dev. 136 (2020), 105123, https://doi.org/10.1016/j.worlddev.2020.105123.
[20] H. Kabir, M. Maple, K. Usher, The impact of COVID-19 on Bangladeshi readymade garment (RMG) workers, J. Publ. Health 43 (2021) 47–52, https://doi.org/10.1093/pubmed/fdaa126.
[21] F. Afridi, A. Dhillon, S. Roy, How has Covid-19 crisis affected the urban poor? Findings from a phone survey, Ideas For India (2020). https://www.ideasforindia.in/topics/poverty-inequality/how-has-Covid-19-crisis-affected-the-urban-poor-findings-from-a-phone-survey.html. (Accessed 17 October 2022).
[22] P. Kumar, S.S. Singh, A.K. Pandey, R.K. Singh, P.K. Srivastava, M. Kumar, M. Drews, Multi-level impacts of the COVID-19 lockdown on agricultural systems in India: the case of Uttar Pradesh, Agric. Syst. 187 (2021), 103027, https://doi.org/10.1016/j.agsy.2020.103027.
[23] M. Gatto, A.H.M.S. Islam, Impacts of COVID-19 on rural livelihoods in Bangladesh: evidence using panel data, PLoS One 16 (2021), e0259264, https://doi.org/10.1371/journal.pone.0259264.
[24] F. Ahmed, A. Islam, D. Pakrashi, T. Rahman, A. Siddique, Determinants and dynamics of food insecurity during COVID-19 in rural Bangladesh, Food Pol. 101 (2021), 102066, https://doi.org/10.1016/j.foodpol.2021.102066.

[25] A.A. Zabir, A. Mahmud, M.A. Islam, S.C. Antor, F. Yasmin, A. Dasgupta, COVID-19 and food supply in Bangladesh: a review, South Asian J. Social Stud. Econ. 10 (2020) 15–23, https://doi.org/10.9734/sajsse/2021/v10i130252.
[26] A. Roussi, Kenya farmers face uncertain future as COVID-19 cuts exports to EU, Financial Times 4. https://www.ft.com/content/05284de8-c19f-46de-9fe7-482689be364b, 2020. (Accessed 17 October 2022).
[27] FAO, Impact of COVID-19 on agriculture, food systems and rural livelihoods in Eastern Africa: policy and programmatic options, Food and Agriculture Organization, Accra, 2020, https://doi.org/10.4060/cb0552en.
[28] H.A.H. Dang, C.V. Nguyen, Gender inequality during the COVID-19 pandemic: income, expenditure, savings, and job loss, World Dev. 140 (2021), 105296, https://doi.org/10.1016/j.worlddev.2020.105296.
[29] L.S. Akalu, H. Wang, Does female-headed household suffer more than the male-headed from Covid-19 impact on food security? Evidence from Ethopia, J. Agric. Food Res. 12 (2023), 100563, https://doi.org/10.1016/j.jafr.2023.100563.
[30] N. Paganini, K. Adinata, N. Buthelezi, D. Harris, S. Lemke, A. Luis, S. Stöber, Growing and eating food during the COVID-19 pandemic: farmers' perspectives on local food system resilience to shocks in Southern Africa and Indonesia, Sustainability 12 (2020) 8556, https://doi.org/10.3390/su12208556.
[31] H.G. Tripathi, H.E. Smith, S.M. Sait, S.M. Sallu, S. Whitfield, A. Jankielsohn, B. Nyhodo, Impacts of COVID-19 on diverse farm systems in Tanzania and South Africa, Sustainability 13 (2021) 9863, https://doi.org/10.3390/su13179863.
[32] A. Mehra, S. Rajput, J. Paul, Determinants of adoption of latest version smartphones: theory and evidence, Technol. Forecast. Soc. Change 175 (2022), 121410, https://doi.org/10.1016/j.techfore.2021.121410.
[33] FAO, Leveraging innovation and technology for food and agriculture in Asia and the Pacific, Food and Agriculture Organization, Bangkok, 2020. https://www.fao.org/3/ca7581en/CA7581EN.pdf.
[34] J.M. Roshetko, N. Pingault, N. Quang Tan, A. Meybeck, R. Matta, V. Gitz, Asia-Pacific roadmap for innovative technologies in the forest sector, Food and Agriculture Organization of the United Nations (FAO), Rome, 2022, https://doi.org/10.17528/cifor/008515. Center for International Forestry Research (CIFOR), Bogor, Indonesia, CGIAR Research Program on Forests, Trees and Agroforestry (FTA).
[35] H.J. Smidt, O. Jokonya, Factors affecting digital technology adoption by small-scale farmers in agriculture value chains (AVCs) in South Africa, Inf. Technol. Dev. 28 (2022) 558–584, https://doi.org/10.1080/02681102.2021.1975256.
[36] H. Munyua, ICTs and small-scale agriculture in Africa: a scoping study, IDRC, 2007. http://www.idrc.ca/uploads/user-S/12212542261Final_Report_HMunya.pdf.
[37] T. Reardon, A. Heiman, L. Lu, C.S.R. Nuthalapati, R. Vos, D. Zilberman, Pivoting" by food firms to cope with COVID-19 in developing regions: e-commerce and "co-pivoting" delivery intermediaries, Agric. Econ. 52 (2021) 459–475, https://doi.org/10.1111/agec.12631.
[38] V. Vardhan, Impact of the COVID-19 pandemic on retailing in emerging countries, Powerpoint presentation published by Euromonitor International, October 2020.
[39] T. Rees, Impacts of the COVID-19 pandemic on food consumption, Powerpoint presentation published by Euromonitor International, October 2020.
[40] D. Turker, C.A. Vural, Embedding social innovation process into the institutional context: voids or supports, Technol. Forecast. Soc. Change 119 (2017) 98–113, https://doi.org/10.1016/j.techfore.2017.03.019.
[41] J.L. Campbell, L.N. Lindberg, Property rights and the organization of economic activity by the state, Am. Socio. Rev. 55 (1990) 634–647. https://www.jstor.org/stable/2095861.
[42] J. Mair, I. Marti, Entrepreneurship in and around institutional voids: a case study from Bangladesh, J. Bus. Ventur. 24 (2009) 419–435, https://doi.org/10.1016/j.jbusvent.2008.04.006.
[43] S.M. Puffer, D.J. McCarthy, M. Boisot, Entrepreneurship in Russia and China: the impact of formal institutional voids, Entrep. Theory Pract. 34 (2010) 441–467, https://doi.org/10.1111/j.1540-6520.2009.00353.x.
[44] D. Miller, J. Lee, S. Chang, I. Le Breton-Miller, Filling the institutional void: the social behavior and performance of family vs non-family technology firms in emerging markets, J. Int. Bus. Stud. 40 (2009) 802–817, https://doi.org/10.1057/jibs.2009.11.
[45] V.K. Narayanan, L. Fahey, The relevance of the institutional underpinnings of Porter's five forces framework to emerging economies: an epistemological analysis, J. Manag. Stud. 42 (2005) 207–223. https://doi/abs/10.1111/j.1467-6486.2005.00494.x.
[46] P.A. Dacin, M.T. Dacin, M. Matear, Social entrepreneurship: why we don't need a new theory and how we move forward from here, Acad. Manag. Perspect. 24 (2010) 37–57. https://www.jstor.org/stable/29764973.
[47] M. Hossain, Frugal entrepreneurship: resource mobilization in resource-constrained environments, Creativ. Innovat. Manag. 31 (2022) 509–520, https://doi.org/10.1111/caim.12502.
[48] P.K. Hota, S. Mitra, I. Qureshi, Adopting bricolage to overcome resource constraints: the case of social enterprises in rural India, Manag. Organ. Rev. 15 (2019) 371–402, https://doi.org/10.1017/mor.2019.19.
[49] C. Sunduramurthy, C. Zheng, M. Musteen, J. Francis, Doing more with less, systematically? Bricolage and ingenieuring in successful social ventures, J. World Bus. 51 (2016) 855–870, https://doi.org/10.1016/j.jwb.2016.06.005.
[50] N. Fligstein, Social skill and institutional theory, Am. Behav. Sci. 40 (1997) 397–405, https://doi.org/10.1177/0002764297040004003.
[51] E.M. Rogers, Diffusion of Innovations, fifth ed., Simon & Schuster, New York, 2003.
[52] D. Kos, R. Lensink, M. Meuwissen, The role of social capital in adoption of risky versus less risky subsidized input supplies: an empirical study of cocoa farmers in Ghana, J. Rural Stud. 97 (2023) 140–152, https://doi.org/10.1016/j.jrurstud.2022.10.027.
[53] E. Pindado, M. Sánchez, Researching the entrepreneurial behaviour of new and existing ventures in European agriculture, Small Bus. Econ. 49 (2017) 421–444, https://doi.org/10.1007/s11187-017-9837-y.
[54] T.L. Albrecht, M.B. Adelman, Communicating Social Support, Sage Publications, Inc., London, 1987.
[55] D. McFadden, The measurement of urban travel demand, J. Publ. Econ. 3 (1974) 303–328, https://doi.org/10.1016/0047-2727(74)90003-6.
[56] M.A. Akudugu, E. Guo, S.K.N. Dadzie, Adoption of modern agricultural production technologies by farm households in Ghana: what factors influence their decisions? J. Biol. Agric. Healthcare 2 (2012) 1–13.
[57] C.A. Wongnaa, D. Awunyo-Vitor, J.E.A. Bakang, Factors affecting adoption of maize production technologies: a study in Ghana, J. Agric. Sci.-Sri Lanka 13 (2018) 81–99, https://doi.org/10.4038/jas.v13i1.8303.
[58] E. Martey, P.M. Etwire, W. Adzawla, W. Atakora, P.S. Bindraban, Perceptions of COVID-19 shocks and adoption of sustainable agricultural practices in Ghana, J. Environ. Manag. 320 (2022), 115810, https://doi.org/10.1016/j.jenvman.2022.115810.
[59] S.K. Kriesemer, P.A. Grötz, Fish for all? The adoption and diffusion of small-scale pond aquaculture in Africa with special reference to Malawi, 2008.
[60] L. Hill, P. Kau, Application of multivariate probit to a threshold model of grain dryer purchasing decisions, Am. J. Agric. Econ. 55 (1973) 19–27.
[61] A. Amsalu, J. de Graaff, Determinants of adoption and continued use of stone terraces for soil and water conservation in an Ethiopian highland watershed, Ecol. Econ. 61 (2007) 294–302, https://doi.org/10.1016/j.ecolecon.2006.01.014.
[62] J.H. Dorfman, Modeling multiple adoption decisions in a joint framework, Am. J. Agric. Econ. 78 (1996) 547–557. https://www.jstor.org/stable/1243273.
[63] K.O. Fuglie, D.J. Bosch, Economic and environmental implications of soil nitrogen testing: a switching-regression analysis, Am. J. Agric. Econ. 77 (1995) 891–900. https://www.jstor.org/stable/1243812.
[64] W.H. Greene, Econometric Analysis, sixth ed., Prentice Hall, New Jersey, 2008.
[65] G. Sabastian, P. Kanowski, D. Race, E. Williams, J.M. Roshetko, Household and farm attributes affecting adoption of smallholder timber management practices by tree growers in Gunungkidul region, Indonesia, Agrofor. Syst. 88 (2014) 257–268, https://doi.org/10.1007/s10457-014-9673-x.
[66] H. Issahaku, B.M. Abu, P.K. Nkegbe, Does the use of mobile phones by smallholder maize farmers affect productivity in Ghana? J. Afr. Bus. 19 (2018) 302–322, https://doi.org/10.1080/15228916.2017.1416215.
[67] R. Rahayu, J. Day, Determinant factors of e-commerce adoption by SMEs in developing country: evidence from Indonesia, Procedia - Social Behav. Sci. 195 (2015) 142–150, https://doi.org/10.1016/j.sbspro.2015.06.423.
[68] R. Misra, R. Mahajan, N. Singh, S. Khorana, N.P. Rana, Factors impacting behavioral intentions to adopt the electronic marketplace: findings from small businesses in India, Electron. Mark. 32 (2022) 1639–1660, https://doi.org/10.1007/s12525-022-00578-4.
[69] B.E. Akinyemi, A. Mushunje, Determinants of mobile money technology adoption in rural areas of Africa, Cogent Social Sci. 6 (2020), 1815963, https://doi.org/10.1080/23311886.2020.1815963.
[70] C.N. Gichuki, M. Mulu-Mutuku, Determinants of awareness and adoption of mobile money technologies: evidence from women micro entrepreneurs in Kenya, Wom. Stud. Int. Forum 67 (2018) 18–22. https://doi:10.1016/j.wsif.2017.11.013.
[71] A. Abdul-Rahaman, A. Abdulai, Mobile money adoption, input use, and farm output among smallholder rice farmers in Ghana, Agribusiness 38 (2022) 236–255, https://doi.org/10.1002/agr.21721.
[72] R.N. Yegbemey, J. Egah, Reaching out to smallholder farmers in developing countries with climate services: a literature review of current information delivery channels, Climate Services 23 (2021), 100253, https://doi.org/10.1016/j.cliser.2021.100253.
[73] R. Sarku, E. Van Slobbe, K. Termeer, G. Kranjac-Berisavljevic, A. Dewulf, Usability of weather information services for decision-making in farming: evidence from the Ada East District, Ghana, Climate Services 25 (2022), 100275, https://doi.org/10.1016/j.cliser.2021.100275.
[74] D. Griggs, M. Stafford-Smith, D. Warrilow, R. Street, C. Vera, M. Scobie, Y. Sokona, Use of weather and climate information essential for SDG implementation, Nat. Rev. Earth Environ. 2 (2021), https://doi.org/10.1038/s43017-020-00126-8.
[75] J. Clements, The value of climate services across economic and public sectors: a review of relevant literature, Technical report, USAID-Engility/International Resources Group (IRG), Washington, 2013, https://pdf.usaid.gov/pdf_docs/PA00KJXW.pdf.
[76] M.H. Kallio, M. Kanninen, H. Krisnawati, Smallholder teak plantations in two villages in Central Java: silvicultural activity and stand performance, For. Trees Livelihoods 21 (2012) 158–175, https://doi.org/10.1080/14728028.2012.734127.
[77] A. Yadav, A. Giri, S. Chatterjee, Understanding the users' motivation and barriers in adopting healthcare apps: a mixed-method approach using behavioral reasoning theory, Technol. Forecast. Soc. Change 183 (2022), 121932, https://doi.org/10.1016/j.techfore.2022.121932.
[78] E. Simelton, M. McCampbell, Do digital climate services for farmers encourage resilient farming practices? Pinpointing gaps through the responsible research and innovation framework, Agriculture 11 (2021) 953. https://www.mdpi.com/2077-0472/11/10/953.
[79] B. Chiputwa, P. Wainaina, T. Nakelse, P. Makui, R.B. Zougmoré, O. Ndiaye, P. A. Minang, Transforming climate science into useable services: the effectiveness of co-production in promoting uptake of climate information by smallholder farmers

in Senegal, Climate Services 20 (2020), 100203, https://doi.org/10.1016/j.cliser.2020.100203.
[80] Republic of Ghana, Electronic Transfer Levy Act, 2022 (Act 1075), Assembly Press, Accra, 2022.
[81] G. Penteriani, The E-Levy in Ghana: Economic Impact Assessment, Groupe Speciale Mobile Association, GSMA, London, 2023.

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