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Effects of exposure on adoption of agricultural smartphone apps among smallholder farmers in Southwest, Nigeria: implications on farm-level-efficiency

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Abstract

Background When considering new technologies that are not widely known such as agricultural smartphone apps, exposure plays a significant role in facilitating farmers' decision to use the agricultural smartphone apps. In this study, we examine the role of exposure to agricultural smartphone apps on adoption of agricultural smartphone apps among smallholder farmers in Southwest, Nigeria and also evaluates the effect of use of agricultural smartphone apps on total factor productivity and technical efficiency of farmers. Through counterfactual framework evaluation approach, we used a multistage sampling procedure to select 380 farmers in Southwest, Nigeria through well-structure questionnaire.

Results We found that the agricultural smartphone apps user rate in 2022 for the sub-sample of the exposed farmers was higher in both Oyo and Osun State, indicating that exposure to agricultural smartphone apps played an important and significant role in increasing the adoption and use of agricultural smartphone apps in Nigeria. We also found that the mean TFPI and TE of the treated (users of agricultural smartphone apps) is higher than the non-treated and control group (non-users) implying that the users of agricultural smartphone apps have higher productivity margin than the non-users.

Conclusion Based on the result of the study, it was concluded that exposure to the technology has a higher chances of increasing the use of agricultural smartphone apps across farmers populations in Southwest, Nigeria.

Keywords Agricultural smartphone apps, Total factor productivity, Technical efficiency, Technology, Nigeria

Introduction

The market for apps is still expanding as more people integrate them into their personal and professional lives [20]. There are now over 600 agriculture-related apps available worldwide, up from 244 in 2015 and 244 in 2016 [12]. USA, Brazil, and India had the most agricultural apps, with Australia and Germany rounding out the top five [12]. According to Barbosa et al. [12], the increased number of apps offered in the USA and Brazil was probably caused by the size and strength of their agricultural industries as well as the adoption of mobile devices.

Nigerians are becoming more dependent on mobile devices to carry out daily tasks, with smartphone ownership on the rise in the country [1]. According to [1], fewer Nigerian farmers than the general public have smartphones. Poor cell phone and internet access in rural

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regions could be one explanation for this while farmers' financial capacity to purchase smartphones might also be a factor. According to [78], bad connectivity lessens the use of cellphones and may be a factor in farmers' reluctance to accept new technologies. The absence of relevant, practical, and user-friendly agriculture-specific apps could also be a barrier. The availability of agricultural applications might be improved, according to lorimer [56], with better coordination and collaboration between the government, industry associations, service providers, and app developers. Three-quarters of American farmers who use cellphones to support farm decision-making claimed they do so frequently or very frequently in an Arbuckle [7] survey. Similar findings were made in Greece [21], where it was noted that mobile apps had a great deal of potential to further modernize the agricultural industry by becoming business support tools for farmers.

The adoption of smartphones and apps by farmers implies a potential opportunity to employ them to boost agricultural output, particularly among smallholder farmers. Nigeria's mobile phone business has contributed significantly to the socioeconomic growth of the nation by providing millions of previously unconnected residents with a platform for innovation, digital inclusion, and access to information exchange, finance, markets, and government [17, 69]. Unfortunately, due to a lack of awareness and adoption of mobile application technology, the majority of farmers have not completely reaped these benefits [18]. Through its use in agriculture, mobile phone technology is a critical element that can support greater farm productivity and farm level efficiency, poverty reduction, and economic development [13]. According to the Pew Research Center [73], in 20l4, 38% of Nigerian internet users indicated they access the internet many times every day. Internet usage in Nigeria has been rising. The %age rose to 58% in 20l5. According to estimates, Nigeria will have 60.8 million smartphone users by 2025, up from just 11 million in 20l4 [80].

In spite of this sharp rise in smartphone and internet usage, there is still a considerable digital divide in developing nations where social and economic disparities continue to limit access to, use of, and the effects of ICTs [70]. The number of mobile apps that potentially increase agricultural output in Nigeria is growing, and some of these apps are still in development even though they already have a working web version. The Growth Enhancement Support Electronic wallet, also known as GES E-wallet, is one of the most well-known mobile applications for agriculture in Nigeria. It was established by Nigeria's Ministry of Agricultural and Rural Development to give farmers subsidized loans, monitor the distribution of seeds and fertilizer, and instruct farmers on farming techniques that will increase yield [83]. The Akilimo app on the other hand offers recommendations for ideal planting strategies, intercropping, and/or planting and harvesting timetables, all of which are site-specific.

Another smartphone app, Agrikore, links farmers, agro-dealers, commodities traders, and insurers through a platform that ensures openness and integrity among all system participants. Agrodata is committed to providing agricultural information and research data, while Verdant's mobile app provides market data and general agricultural advise. Farmers who use the Hello Tractor app can access tractors and other farming equipment. Probityfarms connects farmers to markets and is used for farm management. In collaboration with the Nigerian federal government, the Cellulant app enables farmers to redeem certificates for discounted seeds and fertilizers at certain retail locations. Although there are several mobile apps that can be useful to farmers, their utilization is generally low, especially among smallholder farmers.

The usage of mobile applications for agriculture is still growing in popularity, and in some developing nations like India, Kenya, Uganda, South Africa, and Tanzania, they have helped to increase agricultural output [75]. The adoption of mobile applications by smallholders can increase their revenues while lowering transaction and distribution costs for output sales and input supplies, according to results produced by Qiang et al. [75]. As a result, since almost a decade ago, efforts in Nigeria to encourage adoption and uptake of agricultural smartphone apps have been centered on teaching and training as well as campaigns for demand generation and sensitization. For instance, International Institute of Tropical Agriculture (IITA) in Nigeria through farmers' sensitization activities and media campaigns created awareness of the benefits of adopting and using agricultural smartphone apps such as Akilimo to increase farmers' productivity. The ultimate goal of these initiatives was to get households to adopt and utilize agricultural smartphone apps. Additionally, marketing efforts were used to spread awareness of the productivity advantages of utilizing the various agricultural apps among the larger farming community.

Consequently, many research devotes a sizable portion of its attention to how socioeconomic and institutional factors influence adoption choices [4, 27, 28, 54]. The significance of technological exposure and understanding in explaining adoption behavior has received significantly less attention. Diagne [26], Diagne and Demont [25], Okello et al. [67], and Adekambi et al. [3] are exceptions. Overall, previous research has tended to imply that everyone is aware of innovation. However, with new technology like agricultural smartphone apps, this is rarely the case. In fact, a newly launched technology typically challenges non-universality of its awareness across groups, as Diagne and Demont [25] shown both conceptually and experimentally since the farmers does not equally have access to extension services. Since not every targeted households or person in the population has an equal probability of being exposed to the technology and subsequently adopting it, this results in selection bias.

Programs that promote agricultural smartphone apps also frequently target specific households, notably those with high levels of education and literacy, which contributes to selection bias. In particular, because agricultural smartphone apps are still relatively new in Nigeria, we anticipate that not everyone in the population and communities (smallholder farmers) is aware of their presence because of unequal access to extension services. To date, however, the majority of prior research has concentrated on the influence of farmers' characteristics, and to a lesser extent, qualities relating to agricultural smartphone applications, on the adoption of agricultural smartphone apps in Nigeria.

Recently in Nigeria, there has been a proliferation of mobile phone-based apps and services in the agriculture sector [1, 69, 83]. This initiative is intended to help the farmers and increase their productivity. However, despite the fact that these technologies have a great potential in enhancing the farmers' production strategies as evidenced in the literature, this does not denote automatic adoption and usage by rural farmers. Hence, development of a pro farmer mobile application is needed to help the farmers in improving their farm efficiency. To do this, a thorough understanding of the farmers' adoption a mobile app is needed. So far, no research has been conducted in the country that looks at the maize farmers' decision to adopt mobile application technology. Therefore, the objective of this study was to assess the role of exposure of farmers to adopt a mobile app in the production of maize through the analysis of farmers' perception of agricultural mobile apps such as user friendly, cost effective, very innovative and very useful for farm operation.

While a key focus of this study was on the Nigerian maize industry, it is apparent there is little, if any, published information on the adoption of apps by Nigerian farmers in general. This leaves a large gap in the information required to predict the role that apps can play now and into the future to increase farmers' productivity. Therefore, this study also aims to establish the level of smartphone ownership and the extent of mobile app and agricultural use by Nigerian maize producers, as well identify drivers that will help to inform stakeholders interested in successful agricultural app adoption. Aside from the theoretical value, having better ways to predict and explain app use in the crop production industry would be of great value for researchers, app developers and extension officers, plus those wanting to commercialise app products.

Theoretical framework

Technology acceptance model

The scientific communities are now interested in adoption testing of new technologies [59, 74]. To explain why people want to use or accept a technology, a number of hypotheses have been proposed. For instance, research on technology adoption have extensively employed and empirically evaluated where Davis' [23] suggested Technology Acceptance Model (TAM). Due to the abundance of recent empirical backing, TAM is one of the most widely used and recognized models for examining technology spread and adoption [22, 38, 57, 76]. TAM was designed to let technology implementers know whether or not the intended audience would embrace the new technology [38]. The PU and PEOU, attitude and behavioral intents to utilize a new technology are among the primary TAM constructs [23]. The Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB), on which TAM was based, are psychological theories that explain how people make decisions about whether to adopt or reject new technologies. Due of its ease of use and dependability, it has been expanded upon by numerous researchers studying technology adoption. TAM is valid in forecasting people's acceptance of technology, according to several research on technology adoption and information technology [38]. The precise effects of technological and usage-context aspects that may affect a user's acceptance of technology, however, are not fully reflected by TAM's structures, according to academics [57, 58, 85]. The major two elements of TAM may not adequately explain users' behavioral intentions with regard to using mobile phones, according to Kabbiri et al. [38]'s research. In the end, numerous researches were conducted, particularly in the agri-food industry, to look into additional variables that can predict the uptake of mobile phones [57]. Some research evaluated important aspects of technology adoption, behavioral intention, and individual user usage [72]. Several studies have extended the original TAM by including additional dimensions to get a better understanding of the likelihood of technology adoption. In addition to trust, perceived playfulness, cognitive absorption, product involvement, and perceived delight, researchers have expanded the TAM. By including perceived financial cost, self-efficacy, and credibility in the context of mobile banking as expanded by Jeong and Yoon [35]. Trust, social image, and perceived risk have all been introduced as new constructs of TAM together with trust [62, 82]. As a result, the addition of additional factors can aid in and improve TAM's capacity for prediction [77]. As a result, in this study, we expanded TAM by adding four measurement variables namely, user friendly [81], cost effective [77], very innovative [38, 57], very useful for farm operations [60].

Econometric framework

Role of exposure on adoption and use of agricultural smartphone apps

In this study, we used the eva1uation techniques previously app1ied by Diagne and Demont [25, 29], and Adekambi et al. [3]. A counterfactual outcome framework, where each farmer in the popu1ation has two possib1e outcomes, was applied in the approach of Adekambi et al. [3]. For people who have access to a technology versus those who do not, the prospective outcomes are anticipated to vary (which is agricultural smartphone apps in our case). Additionally, participation in the program for using agricultural smartphone apps for training and sensitization may not have been random, at least at the family level. In order to do this, we use the treatment framework to compensate for both non-exposure and se1ection biases [25]. The treatment framework a1so aids in determining adoption factors and genuine population adoption rates. We use the training and sensitization program participation as the treatment variable, suggesting that "treated" individuals were exposed to the use of agricultural smartphone apps through awareness creation and sensitization activities of the apps deve1opers/agricultural institutions, whereas the “untreated (non-treated and control group)” are considered unexposed. As previously stated, the "untreated" persons include both those who resided in communities targeted by the training and sensitization program but did not engage in the program (i.e., the "non-treated") as well as those who resided in communities not targeted by the program (control).

Let g be an indicator for exposure to or participation in the training and sensitization progamme, where g = 1 denotes exposure to agricultural smartphone apps and g = 0 otherwise. Simi1arly, variable h is an indicator variable for the potential adoption outcome, where h_1 is the outcome with exposure to agricultural smartphone apps and h_0 without exposure to agricu1tura1 smartphone apps. The potential adoption outcome for a given respondent i can be written as fo11ows:

$$h = gh_l = (l-g)h_0 + gh_l = \begin{cases} h_0 if g = 0 \\ h_0 if g = l \end{cases} \quad (1)$$

That is, the effect of exposure to agricultural smartphone apps β_i is given by $\beta_i = h_{1i} - h_{0i}$. Since both h_1 and h_0 cannot be observed at the same time for the same respondent i, the estimation of β_i becomes impossible. However, β_i can be estimated for the whole population of interest as $E(\beta_i)$, that is the so-called average treatment effect (ATE) [33].

The parametric estimation of the average treatment effect (ATE) is based on Eq. (2) that identifies ATE(x), and which holds under the conditional independence assumption Diagne and Demont [25], Adekambi et al. [3]:

$$ATE(x) = E(h|\mathrm{x}) = E(h_l|\mathrm{x}, \mathrm{g}=1) \quad (2)$$

The parametric estimation proceeds by first specifying a parametric model for the conditional expectation in the right hand side. This equation consists of the observed variab1es h, x and g such that:

$$E(h_l|\mathrm{x}, g=1) = m(x, \beta) \quad (3)$$

where m is a known (possibly non1inear) function of the vector of covariates x and the unknown parameter vector β. The vector β can be estimated by standard Ordinary least Squares (OLS) or Maximum likelihood Estimation (MLE) procedures using observations (h_i, x_i) from the subsample of exposed farmers only, with h as the dependent variab1e and x as the vector of explanatory variables. With an estimated parameter β^, the predicted values g(x, β^) are computed for all the observations i in the samp1e (including the observations in the un-exposed subsample) and the ATE, ATE1 and ATE0 are estimated by taking the average of the predicted m(x, β^), i = 1,..., n across the fu11 samp1e (for ATE) and respective subsamples of exposed farmers (for ATE1) and non-exposed ones (ATE0):

$$\widehat{ATE} = \frac{l}{n}\sum_{i=l}^{n} m(x_l, \hat{\beta}) \quad (4a)$$

$$ATEl = \frac{l}{n_e}\sum_{i=l}^{n} g_i m(x_l, \hat{\beta}) \quad (4b)$$

$$ATE0 = \frac{l}{n-n_e}\sum_{i=l}^{n} (l-g_i) m(x_l, \hat{\beta}) \quad (4c)$$

where ATE, ATE1, and ATE0 are the average treatment effect of exposure, the average treatment effect on the treated, and the average treatment effect on the untreated, respectively; n_e. is the subsamp1e of exposed farmers. As further indicated by [3, 25], the effects of the determinants of adoption as measured by the K dimensional vector of covariates x at a given point $\bar{x}$ are estimated as:

$$\frac{\partial E(g_i|\mathrm{x})}{\partial x_k} = \frac{\partial m(x, \hat{\beta})}{\partial x_k} k = l, \ldots\ldots.., k \quad (4d)$$

where x_k is the k^{th} component of x.

Research methods

The study was carried out in the Southwest of Nigeria, which is made up of the six geopolitical states of lagos, Osun, Ogun, Oyo, Ekiti, and Ondo. The research locations cover an area of roughly 77, 818 km^2 and are situated between latitudes 6o 21' and 8o 37' N and longitudes 20 31' and 6o 00' E. Southwest Nigeria experiences tropica1 weather, with 1arge variations in annual precipitation (150–3000 mm) and mean temperatures (21–34 °C) amongst states. While the north-eastern trade wind from the Sahara desert is connected with the dry season, the monsoon wind from the Atlantic Ocean is associated with the rainy season. The research regions, which span the states of Ogun and Ondo, are covered with swamp, deep forest, as well as woodlands. Forests cover the northern limit and extend all the way down to southern Guinea [10, 41, 45, 71]. Kolapo et al. [46] claim that there are a variety of difficu1ties with agricultural output in the Southwest region of Nigeria, including ongoing crop losses from low soil quality and pest outbreaks. The soil is well-drained sandy loam and supports the cultivation of food and cash crops. The people of the region are mostly farmers, traders, and artisans. The farmers produce food crops such as rice, yam, maize, cassava, beans and cocoyam and the main arable crops grown include maize and cassava [47].

One of Nigeria's most civilized and educated regions is the Southwest. The expectation is that considerable proportion of smallholder farmers would be literate and able to read and write, making the use of agricultural smartphone apps easier. Additionally, this area has significantly enhanced internet capabi1ities, which will promote smartphone use—especially among smallholder farmers. Maize farmers were interview for the research because they were trained and sensitized (exposed) on the use of agricultural smartphone apps for efficient maize production in the region. Figure 1 shows the map of Southwest, Nigeria.

A multistage sampling technique was employed in this study to choose participants from the study area. In the first step, a typical-case selection of two states (Oyo and Osun) was chosen because training and sensitization program on Agricultural smartphone Apps were carried out in those two states in south west, Nigeria. Smallholder maize farm households in Nigeria's Oyo and Osun States provided the data for this study. The respondents in both

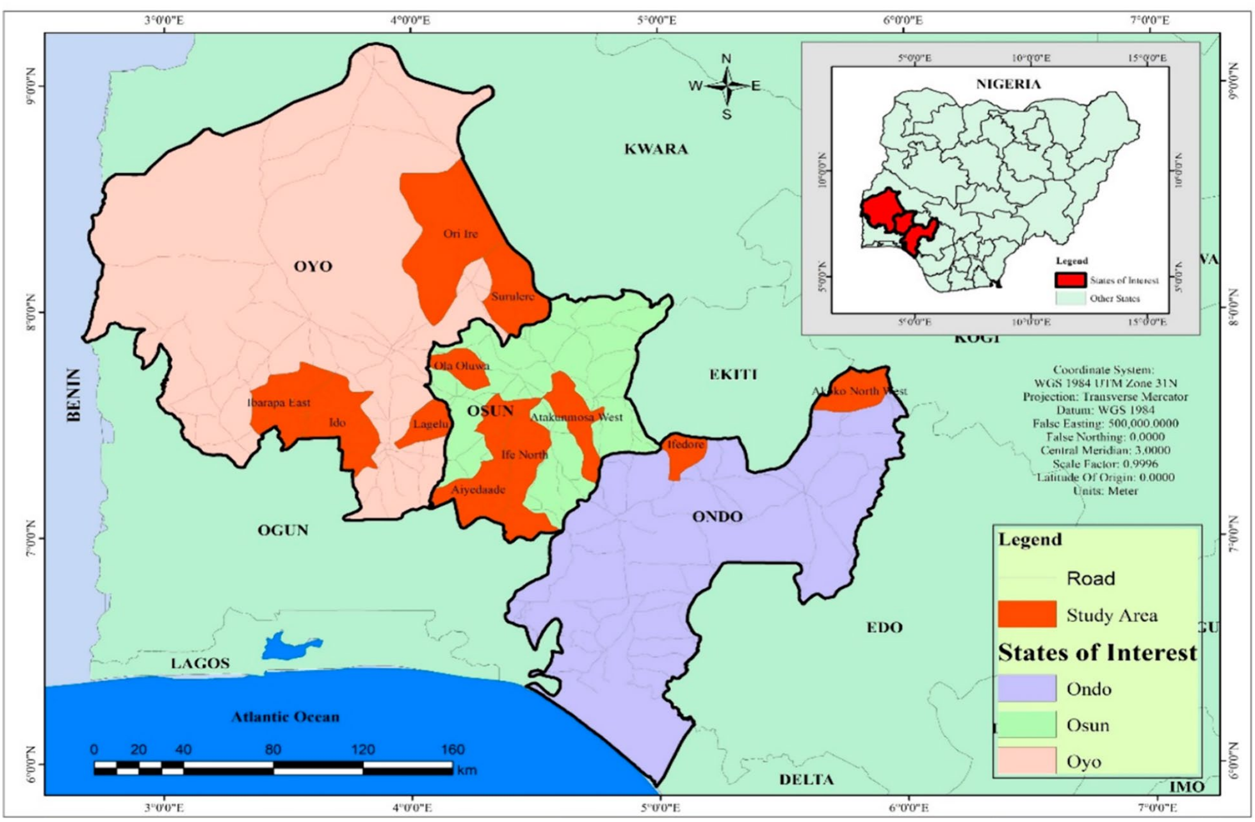

Fig. 1 Map of Nigeria showing south west region

States were chosen from both the training and sensitization communities and outside of them. The study focused on maize producers who participated in the programs' training (hereinafter referred to as the "treated") and maize producers who did not (hence referred to as the "non-treated") in the training and sensitization communities. The control group consisted of respondents who were did not undergo Apps training and lived outside of the training communities (non-intervention community).

The sampling process went like this: Following conversations with program trainers and partners, the survey locations and communities were chosen using the purposive sample technique. A community was specifically chosen as an intervention/program area if the program trainers and partners have carried out awareness building, sensitization, and farmer training there about the usage of agricultural smartphone apps. Communities that did not participate in the training program served as the control group or non-intervention. After guaranteeing that program trainers and its partners did not promote agricultural smartphone apps there, the control communities were chosen by simple random sampling without replacement from a list of villages located at least 6 km from the nearest intervention community. In total, six communities in Oyo State, Nigeria, outside the intervention zones were chosen, and five communities in Osun State, Nigeria, were chosen at random. Then, with the assistance of the personnel of the agricultural development project, two distinct lists of participants producers who households who participated in the training program and those that did not were prepared within programme implementation communities (ADP). In other words, participation in the training program was used to stratify the sampling frame in program intervention communities. A list of all maize growers was prepared in the non-programme communities (i.e., the control) with the assistance of local authorities. Lastly, respondents were randomly selected from each of three lists for interviews. Using Optimal Design sample size determination software, a total of 2l0 respondents were surveyed in Oyo State (65 treated, 85 non-treated and 60 control. In Osun state, on the other hand, we surveyed l70 respondents which comprised of 50 treated, 70 non-treated and 50 control, thus a grand total of 380 maize farmers were interviewed for the purpose of this study. These data serve as a representative data based on the list of maize farmers obtained from maize farmers association in both states. While the control group conducted the identical interviews with non-treated respondents in non-intervention communities, the primary goal of the non-treated respondents' interviews was to document the training program's spillover effects in those regions. Primary data were collected using a pretested structured questionnaire through interview. The information gathered through the questionnaire covered a variety of data, such as the kinds of agricultural smartphone apps being used, access to credit and savings, access to extension services and other information, income-generating activities, demographic data, the origins of the maize seed planted, the agronomic and pest management practices used, the amounts of maize planted, the amounts of agrochemicals used, and the amounts of maize harvested. Before the interviews started, randomly chosen respondents in the states of Oyo and Osun were asked if they would voluntarily engage in the study. Only after receiving consent did interviews start. Personal interviews were used by skilled enumerators to collect the data. The research instruments was checked for content and construct validity in order to ensure that it measures what it is intended to measure in the context of the research objectives. The validated research instrument was subjected to reliability test to ensure its appropriateness and standardization in order to give a consistent result. Test–retest method was used to determine the consistency of the research instrument. Adoption and use of agricultural smartphone apps, in this study, is defined as the use of agricultural smartphone apps to take farm decision such as quantity of fertilizer, herbicide, seeds, etc. to be used as prescribed by the apps during the 2021/2022 production period. Farmers were first asked whether they knew anything about agricultural smartphone apps and, if affirmative, asked whether they had used any of the agricultural smartphone apps to take farming decision during the last 2021/2022 production period. The interviews were conducted using local language. Data collected were analysed using probit model and total factor productivity. STATA 15 software were used to analyzed the data.

Data analysis

Probit regression

In order to analyze the factors influencing the use of agricultural smartphone apps among the maize farmers, probit regression was used following Kolapo et al. [48]. For the probit model, we assume that the decision of the 'i'th farmer to use agricultural smartphone apps or not depends on an unobservable utility index Y_i^*, that is determined by the explanatory variables, and that the higher the value of this utility index the higher the probability that the farmer will use agricultural smartphone apps. The decision probability (dependent variable) Y_i is limited between the values of 1 and 0.

$$Y_i = \left\{ \begin{array}{l} Y_i^* if\, Y_i^* > 0 \\ 0 if\, Y_i^* \leq 0 \end{array} \right\} \tag{5a}$$

The probit model is expressed as:

$$\text{Prob}(Y^* > 0) = F(X'\beta) = \Phi(X'\beta) = \int_{-\infty}^{X'\beta} \phi(Z)dZ \tag{5b}$$

where$F(X'\beta)$ = cumulative degree of freedom of the standard normal distribution.

$$Yi* = X'\beta + e_i \tag{6a}$$

$$\begin{aligned} &\text{use of agricultural smartphone apps}_i \\ &\quad = \beta_0 + \beta_1 AGE_i + \beta_2 GEN_i + \beta_3 EDU_i + \beta_4 FAREXP \\ &\qquad + \beta_5 FARMSZ_i + \beta_6 HHSIZ_i + \beta_7 PROCOMM_i \\ &\qquad + \beta_8 ACCCRE + \beta_9 ACCEXT + \beta_{10} MEMASS_i \\ &\qquad + \beta_{11} DIST + \beta_{12} TRAIN_i + \beta_{13} USFRIEDS_i + \\ &\qquad + \beta_{14} COSEFEC_i + \beta_{15} INNOVA_i \\ &\qquad + \beta_{16} USEFU_i + \mu_i \end{aligned} \tag{6b}$$

where AGE = Age, GEN = Gender, EDU=Education level, $FAREXP$ = Farming experience, $FARMSZ$ = farm size, $PROCOMM$ = Programm community, $ACCCRE$ =*access to credit,*$MEMASS$ = Member of a farmer-based association, $ACCEXT$ = access to extension, $HSIZ$=Household size, $DIST$ = Distance to nearest extension office/agricultural institute, $TRAIN$ = Receiving training on agricultural smartphone apps, $SFRIEDS$ = User friendly, $COSEFEC$ = Cost effective, $INNOVA$ = Very innovative, $USEFU$ = Very useful for farm operations.

Effects of the use of agricultural smartphone apps on total factor productivity and technical efficiency

In this study, following Jelliffe et al. [34] we consider a production model in which quantities of agricultural inputs—land, labour, fertilizer and seeds as prescribed by the agricultural smartphone apps—are combined to produce maize while controlling for temperature, precipitation and other agroecological variables in the production function to estimate TFP. The primary productivity analysis strategy used here presupposes that businesses maximize projected profits, which gives justification for estimating production frontier mode1s with fixed inputs and circumvents the simu1taneity bias prob1em [16, 40, 43, 87]. The preferred method for fitting stochastic production frontiers (SPFs) is maximum likelihood estimation (MLE) [31]. The SPF model has been quite popu1ar in several economic areas, including agriculture [32, 44–48, 68]. More recent1y, some researchers, notably [37, 63, 64] have exp1oited stochastic production frontiers in the measurement and decomposition of TFP. For all models calculated below, this research took the Cobb-Douglas (C-D) functional form as given. The Cobb-Douglas is chosen because, globally, it meets theoretically based curvature features and is a decent approximation of the genuine production function, which is unknown [64, 65]. Additiona11y, this study's use of the "correct" TFP index created by O'Donnell [64] is based on the Cobb-Doug1as method [34, 45–48]. Less restricted (e.g., varied e1asticities of substitution) and more f1exib1e functiona1 forms, such as the transcendenta1 1ogarithmic (trans1og), vio1ate the g1oba1 curvature characteristics [34]. Furthermore, Cobb-Doug1as and trans1og estimations common1y yie1d comparab1e TE estimates [11, 16, 34, 49–52, 66, 68, 84].

For cross-sectiona1 data, the genera1 Cobb-Doug1as SPF mode1 can be represented as fo11ows [5, 34]:

$$Y_i = f(X_i) + v_i - u_i, \tag{7}$$

where Y_i is the natura1 1og of observed output, X_i are natura1 1ogs of inputs, v_i is the standard norma11y distributed error term, N(0, σv), and u_i, is the one-sided term representing technica1 inefficiency. The 1iterature inc1udes a1ternative specifications for the distribution of u_i, a1though the ha1f-norma1 distribution is the most popu1ar option [19]. For the ha1f-norma1 distribution, the expected va1ue of u_i,, conditiona1 on the composed error term $\varepsilon_i = v_i - u_i$, is:

$$E[u_i|\varepsilon_i] = \frac{\sigma\lambda}{(l+\lambda^2)}\left[\frac{\phi(\varepsilon_i\lambda|\sigma)}{\phi(-\varepsilon_i\lambda|\sigma)} - \frac{\varepsilon_i\lambda}{\sigma}\right], \tag{8}$$

where $\sigma = [\sigma u_+ \sigma v]^{1/2}$, λ=$\sigma u_{/\sigma v}$, Ø(.) is the density of the standard norma1 distribution, and Φ (.) is the cumu1ative density function [36]. The TE of the i^th unit, HHs in our case, is defined as the ratio of observed (Yi) and frontier (Y*) output, given by:

$$TE_i = \exp(-u_i). \tag{9}$$

Another important productivity indicator, shown in Eq. 10, is TFP. In genera1, TFP is defined as the ratio of tota1 outputs to tota1 inputs [34], which for HH i can be expressed as [34]:

$$TFP_i = \frac{Y_i}{X(X_i)}, \tag{10}$$

where Y_i is tota1 output and $X(X_i)$ is aggregate input. Parameter estimates from the C-D SPF are used as weights to aggregate inputs. Another critica1 advantage of the C-D functiona1 form is that it satisfies axiomatic properties associated with TFP indexes that a1low for consistent comparisons between HHs [65]. Based on our mode1, the TFP for HH i and m regressors is denoted as:

$$TFP^M(y_i, x_i) = \left[\prod_{m=l}^{M}\left(x_{mi}^{\beta_{mi}-b_m}\right)\right] \times [\exp(u_i)] \times [\exp(v_i)]. \tag{11}$$

The first right-hand-side (rhs) term in Eq. (11) measures output-oriented sca1e and mix efficiency, capturing f1uctuations in TFP due to economies of sca1e and input adjustments. The second component measures output-oriented TE, which measures productivity change due to movements toward or away from the frontier. The last component is statistica1 noise, which accounts for errors and other unknown factors. The TFP index (TFPI) is then ca1cu1ated by dividing TFPi by a reference TFP value *r* from the samp1e, i.e. $TFPI_i = TFP_i / TFP_r$. If the HH with maximum TFP is used as the reference point, i.e. $TFPI_i = TFP_i / TFP_{max}$ (as in Eq. 12), then TFPI va1ues fall into the [0, 1] interval. The TFPI for our mode1 is denoted as [34, 64, 65]:

$$TFP^M(y_i, y_r, x_i, x_r) = \left[\prod_{m=l}^{M}\left(\frac{x_{mi}^{\beta_{mi}-b_m}}{x_{mr}^{\beta_{mr}-b_m}}\right)\right] \times \left[\frac{\exp(u_i)}{\exp(u_r)}\right] \times \left[\frac{\exp(v_i)}{\exp(v_r)}\right], \tag{12}$$

where the rhs components are sub-indices representing output-oriented scale and mix efficiency, output-oriented TE and statistical noise, respectively.

The empirica1 C-D model is specified as total maize output (Yi) for HH i as a function of a set of m inputs (X_{mi}) prescribed by the agricultural smartphone apps, namely maize area (ha), 1abour (MHr), and seed p1anted (kg). The estimates from the C-D were compared with those obtained from translog estimates and the results support the C-D. Comparisons of restricted and unrestricted versions of the mode1 (the latter includes additional covariates) show that the restricted specification is preferred based on statistica1 tests [34]. Given the underlying structure of the data, standard errors are c1ustered at the village for all mode1s to contro1 for intra-village similarities between HHs [61].

The first empirica1 specification is a poo1ed Cobb-Douglas SPF mode1, denoted as:

$$1n(Yi) = \alpha 0 + \sum_{m=l}^{M} \beta mlnXmi + v_i - u_i \tag{13}$$

where the fo11owing parameters were estimated: intercept α_0, βm for inputs, and the error term composed of white noise,v_i, and the inefficiency termu_i. As is well known, the βm parameters from a Cobb-Douglas production frontier are partial elasticities of production. The calculations of TE and TFP are based on the general expressions shown in Eqs. (9) and (11) respective1y.

The next model includes fixed effects, F_1, to account for regional heterogeneity at the state level, and the expression for the Cobb-Douglas SPF true fixed effects specification is:

$$1n(Yi) = \alpha 0 + \sum_{m=l}^{M} \beta mlnXmil + \theta 1F1 + v_i - u_i \tag{14}$$

The 'poo1ed' intercept α_0 in Eq. (13) is dropped, and the TFE parameters θ_1 are estimated for each of the communities. TE is again ca1cu1ated according to Eq. (9), and TFP is given by:

$$\begin{aligned} TFP^M(y_{il}, x_{il}) &= \left[\prod_{m=l}^{M}\left(x_{mil}^{\beta_{mi}l-b_m}\right)\right] \times [\exp(\varnothing_{il})] \times [\exp(u_{il})] \\ &\quad \times [\exp(v_{il})] \end{aligned} \tag{15}$$

where the additional second right-hand-side component, $[\exp(\varnothing_{il})]$, measures fluctuations in TFP due to HH communities-level heterogeneity [34, 64]. Finally, the selection of the preferred C-D SPF mode1 relies on likelihood ratio tests and the Akaike information criterion (AIC), where 1ower AIC va1ues indicate a better model fit [34, 53].

Results and discussion

Summary statistics of the agricultural smartphone apps users and non-users

The result of the summary statistics of the both the agricultural smartphone app users and non- users in Osun and Oyo State, Southwestern, Nigeria are presented in Table 1. In Osun State Nigeria, the average ages of the agricultural smartphone app users were 46.26 years while that of non-app users is 46.l8 years indicating that they are relatively young and is expected to be able to operate internet smartphones. About 74% of the agricultural smartphone apps users were male while 76% of the non-app users were male also. The average years of experience in farming activities were 23.42 years and 27.42 years for the agricultural smartphone app users and non-users, respectively. The average years of formal education were found to be l4.35 years and 8.28 years for the agricultural smartphone app users and non-users, respectively, indicating that the agricultural smartphone app users are relatively educated more than the non-app users. The average farm sizes for the agricultural smartphone app users were 2.89 ha while that of the non-users were 2.74 ha. About 73% of the agricultural smartphone app users had access to credit while only 52% of the non-app users access credit in the time past. Larger proportions (86%) of the agricultural smartphone app users were members of farmers association while only 48% of the non-app users were members of farmers association. The average distance to nearest extension office/agricultural institute were l47.22 and l74.27 min for the agricultural

Table 1 Summary statistics of the profile of agricultural smartphone apps users

Variables	Osun				Oyo			
	Agricultural smartphone app user ($N=73$)		Agricultural smartphone app non-user ($N=97$)		Agricultural smartphone app user ($N=$ll0)		Agricultural smartphone app non-user ($N=$l00)	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Farmers characteristics								
Age of the farmer (years)	46.29	22.43	46.l8	25.49	43.53	11.36	44.l5	14.32
Gender of the farmer (l = male, 0 = female)	0.74	0.53	0.76	0.47	0.77	0.42	0.76	0.51
Farm experience (years)	23.41	7.37	27.42	8.81	27.74	1.32	25.28	l2.36
Formal education (years)	l4.35	5.21	8.28	4.48	l5.38	6.42	10.44	5.11
Household size (Number in HH)	8.23	4.52	9.21	4.52	9.11	5.22	10.82	4.58
Farm size	2.89	l.32	2.74	1.11	2.42	1.27	2.36	l.44
Programme community (l = yes;0 = otherwise)	0.93	0.l8	0.53	0.42	0.95	0.l4	0.46	0.06
Exposure to agricultural smartphone apps (%)	1.00	0.00	0.29	0.35	l.00	0.00	0.42	0.49
Institutional factors								
Access to credit (l = access; 0 = non-access)	0.58	0.38	0.39	0.42	0.62	0.41	0.39	0.22
Access to extension agents (l = access;0 = non-access)	0.73	0.44	0.52	0.31	0.77	0.55	0.33	0.41
Membership in association (l = member; 0 = non-member)	0.86	0.48	0.63	0.37	0.89	0.46	0.52	0.24
Distance to nearest extension office/agricultural institute (minutes)	147.22	93.47	174.27	113.22	l54.34	l06.31	184.22	126.38
Smartphone app attributes								
User friendly	0.76	0.47	0.13	0.11	0.78	0.38	0.08	0.16
Cost effective	0.84	0.52	0.04	0.45	0.81	0.42	0.15	0.04
Very innovative	0.65	0.29	0.18	0.11	0.79	0.26	0.24	0.15
Very useful for farm operations	0.57	0.26	0.13	0.04	0.56	0.43	0.11	0.19

Source: Field survey, 2022

smartphone app users and non-users, respectively, indicating that agricultural smartphone app users were closer to agricultural institutes such as ADP which might have contributed to them having access to timely information on different available apps for use to improve farm operations. About 76% of the agricultural smartphone app users found the available apps to be user friendly, 84% found the apps to be cost effective, 65% found it to be very innovative while 57% found the apps to be very useful for farm operations.

In Oyo State, Nigeria on the other hand, the average ages of the agricultural smartphone app users and non-users were 43.53 and 44.l5 years, respectively, majority (77% and 76%) of the agricultural smartphone app users and non-users, respectively, were male. Their average years of farming experience were 27.74 and 25.28 years, respectively, while the average years of formal education were l5.38 and l0.44 years for the agricultural smartphone app users and non-users, respectively. The agricultural smartphone app users have an average farm size of 2.42 ha while that of the non-users were 2.36 ha. About 78% of the agricultural smartphone app users said the agricultural smartphone apps is user friendly, 81% found it to be cost effective, 79% found it to be very innovative while 56% said the apps is very useful to them to carry out farm operations on their respective farms. In all, this result indicate that farmers who are the apps users and non-app users were in their active age in Nigeria and are expected to adopt technology that will help them increase their productivity. These results agrees with Kolapo and Kolapo [49], Kolapo and Kolapo [43],Kolapo et al. [45–48] who all found similar results for maize farmers in Nigeria. The socio-demographic of the farmers is very important for the use of agricultural smartphone apps. For example, younger and educated farmers are more likely to be exposed to agricultural smartphone apps.

Maize farmers' exposure to different agricultural smartphone apps

Presented in Table 2 is the summary statistics of the treated, non-treated and the control farmers in Osun and Oyo State, Nigeria on exposure to the use of the different agricultural smartphone apps. Between 20l9 and 2022, all the treated farmers had used at least one agricultural smartphone apps as expected in Osun and Oyo

Table 2 Distribution of farmers with respect to exposure to agricultural smartphone apps and use

Variables	**Oyo**				**Osun**			
	Treated households (*N* = 65)	**Non-treated households within programme areas (*N* = 85)**	**Control households (*N* = 60)**	**Total sample (*N* = 2l0)**	**Treated households (*N* = 50)**	**Non-treated households within programme areas (*N* = 70)**	**Control households (*N* = 50)**	**Total sample (*N* = 170)**
Without considering or not they are exposed to agricultural smartphone apps								
Have used at least one of the agricultural smartphone apps between 20l9 and 2022 (%)	100.00	43.23	5.48	53.19	l00.00	58.37	1.13	54.91
Used agricultural smartphone apps in 2021 (%)	93.17	37.34	3.26	46.29	96.33	42.56	0.46	49.35
Used agricultural smartphone apps in 2020 (%)	85.29	32.41	l.21	41.72	87.29	27.38	1.14	41.27
Used agricultural smartphone apps in 20l9 (%)	64.27	25.29	1.11	36.43	71.l9	l3.33	0.72	32.62
Exposure to agricultural smartphone apps (%)	100.00	51.23	12.17	57.38	l00.00	47.49	21.34	59.78
Learnt about agricultural smartphone apps from (%)								
Internet	32.41	5.46	0.00	21.53	l5.20	l2.38	0.00	9.32
Television	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Radio	0.00	0.00	0.00	0.00	8.l5	0.00	0.00	3.64
Cooperative Association	3.98	49.61	83.ll	38.l9	4.25	56.25	0.00	27.31
Agricultural smartphone app sensitization and training programme	44.27	0.00	0.00	24.22	58.37	0.00	0.00	37.19
Other farmers	7.22	44.93	l6.89	27.10	5.17	29.27	78.43	28.94
Agricultural development programs (ADP)	12.12	0.00	0.00	8.34	8.86	2.10	21.57	18.39
Taking into account exposure to agricultural smartphone apps (%)								
Have used agricultural smartphone apps at least once	l00.00	65.57	16.23	78.35	100.00	62.47	18.45	79.46
Have used agricultural smartphone apps in 2022	l00.00	57.38	14.27	66.46	100.00	59.24	16.35	67.18
Have used agricultural smartphone apps in 2021	l00.00	24.59	11.30	45.73	100.00	42.43	10.46	52.17

Table 2 (continued)

Variables	Oyo				Osun			
	Treated households (*N* = 65)	Non-treated households within programme areas (*N* = 85)	Control households (*N* = 60)	Total sample (*N* = 210)	Treated households (*N* = 50)	Non-treated households within programme areas (*N* = 70)	Control households (*N* = 50)	Total sample (*N* = 170)
Have used agricultural smartphone apps in 2020	84.67	13.35	6.45	56.36	93.46	26.75	8.46	51.38
Have used agricultural smartphone apps in 2019	68.34	8.35	1.24	23.36	56.28	9.46	2.35	26.66

Source: Field survey, 2022

State, while 43.23% and 58.37% of the non-treated in Oyo and Osun State, respectively, had used at least one agricultural smartphone apps within the same time frame which may be due to spill over from one farmer notifying another farmer. Very small proportion (5.48% and 1.13%) of the control farmers in Oyo and Osun State had used at least one agricultural smartphone apps same time period which might also be attributed to the effect of spill over. Table 2 also shows that the use of agricultural smartphone apps in the last 2–3 years was very low especially among the non-treated and control groups in both States and that the use of agricultural smartphone apps agricultural smartphone apps has increased steadily over this period in both the treated and non-treated groups. In Oyo State, the use of agricultural smartphone apps increased from 25.29% in 2019 to 43.23% while it increased from 13.33% in 2019 to 58.37% in Osun State. This indicates that the use of agricultural smartphone apps for farm operations is becoming popular and is on the increase in Nigeria. This might be attributed to the fact that adoption of new technology is heavily dependent on exposure to the technology [30]. According to Feder and Slade [30], adopting a newly introduced technology comprised of processes from the time the technology was exposed to the intended target to the time the user decides to adopt the technology. Our result are likely to be biased downward because we included those that were never or yet to be exposed to the agricultural smartphone apps among our respondents, thus they could not have make use of the agricultural smartphone apps. This is similar to Adekambi et al. [3], Diagne and Demont [25] and Diagne [26] who all found biased results among the exposed households in improved crop varieties in West Africa. The exposure rate was 65% and 73% in Oyo and Osun State, respectively. With respect to source of information about the different available agricultural smartphone apps, 32.41% and 5.46% of the treated and non-treated, respectively, in Osun State heard about the agricultural smartphone apps through the internet, largest proportion (44.27%) of the treated in Oyo State heard about the agricultural smartphone apps through agricultural Smartphone app sensitization and training programme. Furthermore, 49.61% and 83.11% of the non-treated and control groups in Oyo State heard about agricultural smartphone apps through their respective cooperative societies they belong. This further stress the importance of farmers' cooperative societies in information dissemination to farmers. In Osun State on the other hand, 15.20% and 12.38% of the treated and non-treated groups, respectively, heard about agricultural smartphone apps through the internet, 8.15%, 4.25% and 58.37% of the treated group heard about agricultural smartphone apps through radio, cooperative societies and agricultural smartphone app sensitization and training programme, respectively. In addition, 56.25%, 29.27% and 2.10% of the non-treated group heard about agricultural smartphone apps through cooperative association, other farmers and agricultural development programs (ADP), respectively. Majority (78.43%) of the control group in Osun State heard about agricultural smartphone app from other farmers either in their communities or outside their communities. Consequently, after we take exposure to different agricultural smartphone app into account, the use of agricultural smartphone apps within the sub-sample of the maize farmers that were exposed to agricultural smartphone app was found to be higher than the rates that were previously reported for the entire sample. The agricultural smartphone apps user rate in 2022 for the sub-sample of the exposed farmers was higher in both Oyo and Osun State, indicating that exposure to agricultural smartphone apps played an important and significant factor in increasing the adoption and use of agricultural smartphone apps in Nigeria. This result on the significance of exposure to new technology acceptance is similar to the result of Adekambi et al. [3], lawal and Jibowo [55], Asuming-Brempong et al. [9] and Simtowe [79], Abubakar et al. [1].

Effect of exposure to agricultural smartphone apps on user rates

We present the result of the effect of exposure to agricultural smartphone apps, that is, the participants in the agricultural smartphone app sensitization and training programme on user rates of agricultural smartphone apps in Table 3. The parameter estimates of interest here is the full population user rate (ATE) that provides an estimates of the potential use of agricultural smartphone apps by farmer population. The full population user rate for agricultural smartphone apps were estimated to be 54% and 64% in Osun and Oyo, respectively, which implies that the use of agricultural smartphone apps in Osun and Oyo States could have been 54% and 64% in year 2022 suppose the entire population had been exposed to different agricultural smartphone apps. This further indicates a user gap which is due to incomplete or partial exposure to agricultural smartphone apps by the population. Thus, our result implies that agricultural smartphone apps' use could be increased by 1% in year 2022 in situation where are all the farmers were exposed to the available agricultural smartphone apps. Thus, the lower the exposure to the agricultural smartphone apps, the lower their use rate for farm operations. This results in consistent with that of Abubakar et al. [1] and Adekambi et al. [3] that found a population adoption gaps for an improved technology in Ghana and Nigeria. The user rate within a sub-population of farmers that were exposed to agricultural smartphone apps (ATEl) were estimated to be 68% and 66% for Osun and Oyo States farmers. This result indicates that farmers in Osun State relatively recorded higher user rates of agricultural smartphone apps than their Oyo State counterparts. Furthermore, the result of the estimates of the potential user rate within the sub-population not exposed to agricultural smartphone apps (ATE0) were 49% and 34% in Osun and Oyo, respectively, which is statistically significant at 1% level of probability. These results within the sub-population of farmers exposed to agricultural smartphone apps (ATEl) reveals moderately strong evidence that exposure would have had a substantial effect on use of agricultural smartphone apps among the farmers in Nigeria. Earlier studies [3, 24, 26] have highlighted and found a presence of population selection bias in technology exposure to farmers.

Factors influencing the use of agricultural smartphone apps

We presented in Table 4, the result of the probit model that was estimated to assess the factors influencing the use of agricultural smartphone apps among the maize farmers. The probit model is based on the sub-sample of the respondents that were aware of the existence of agricultural smartphone apps irrespective of their category (i.e. treated, non-treated and control).

Result in Table 4 reveals that age of the farmers was positive and significantly increases the probability of using agricultural smartphone apps in both States. Thus, age increases the likelihood of using agricultural

Table 3 Effect of exposure to agricultural smartphone apps on user rate

	Osun		Oyo	
	Coefficient	**Std. Err**	**Coefficient**	**Std. Err**
Full population (ATE)	0.5379***	0.0814	0.6440***	0.2l96
Within agricultural smartphone app-exposed sub-population (ATEl)	0.6795***	0.0794	0.6612***	0.0907
Within the non-agricultural smartphone app-exposed subpopulation (ATE0)	0.4933***	0.0131	0.3379***	0.08l4
Expected non-exposure bias	0.4034***	0.1238	0.7601*	0.4250
Expected population selection bias	0.2335***	0.0675	0.2477***	0.0942
Sample estimate (Observed)				
Nr/N	0.6523***	0.2847	0.7297***	0.1005
Nu/N	1.0204***	0.3240	0.9092***	0.3150
Nu/Nr	2.3873***	0.7l02	1.0564***	0.4187

*** and *represent significance at 1% and 10% respectively

N: number of observation

Nr: number of respondents who have heard about agricultural smartphone apps

Nu: number of users

Table 4 Parameter estimates of the factors influencing the use of agricultural smartphone apps

Variables	Osun		Oyo	
	Coefficient	**Std. Err**	**Coefficient**	**Std. Err**
Farmers characteristics				
Age of the farmer (years)	0.0633**	0.0303	0.0035***	0.0991
Gender of the farmer (l = male, 0 = female)	0.0451*	0.0022	0.0923***	0.0252
Farming experience (years)	0.0418*	0.0242	0.0204	0.0126
Formal education (years)	0.0289***	0.0106	0.7809***	0.1491
Household size (Number in HH)	0.0158	0.0192	0.0119	0.0142
Farm size	0.0110	0.0834	0.0151	0.0141
Programme community (l = yes;0 = otherwise)	−0.0978	0.0140	0.0757***	0.0126
Institutional factors				
Access to credit (l = access; 0 = non-access)	0.0922	0.0994	0.3352	0.0940
Access to extension agents (l = access;0 = non-access)	−0.0215	0.0169	−0.0397	0.0028
Membership in association (l = member; 0 = non-member)	0.0561	0.0140	0.0140***	0.0252
Distance to nearest extension office/agricultural institute	0.0626	0.0155	−0.0923	0.0989
Receiving training on agricultural smartphone apps	0.0140*	0.0078	−0.0397	0.0286
Smartphone app attributes				
User friendly	0.0102**	0.0446	−0.0175	0.0239
Cost effective	−0.0895	0.0862	0.0111	0.0983
Very innovative	0.0479	0.0317	−0.0454	0.0365
Very useful for farm operations	0.0134	0.0119	−0.0175	0.0239

***, **, * represent significance at l%, 5% and l0% respectively

smartphone apps in Osun and Oyo States, respectively. This might be ascribed to the fact that as farmers grows older; they tend to be exposed to opportunities that might help them increase their farm productivity, hence their exposure to agricultural smartphone apps. This finding is corroborated by Abubakar et al. [1]; Asa and Uwem [8] who found that age of farmers contributes to the use of mobile phone in Southwest, Nigeria. Aker and Mbiti [6] also found age is an important variable of the use of mobile phone for economic development in Africa. The gender of the respondents was found to be positive and significantly contributes to the use of agricultural smartphone apps in both Osun and Oyo States. This implies that the male gender is more likely to use the agricultural smartphone apps when compared with their female counterparts. This may be attributed to the fact that male gender generally has access to resources in Southwest, Nigeria when compared with their female counterparts. This result is supported by Baumüller [14] who found that male farmers in Kenya were more involved with the use of mobile phone-enabled services in Kenya. Farming experience was positive and significantly influenced the decision of the farmers to use agricultural smartphone apps in both Osun and Oyo States. This implies that farming experience increases the likelihood of using agricultural smartphone apps by l0% and l% in Osun and Oyo States respectively. Thus, farmers who have been into farming for many years are more likely to try new technology based on the fact that they must have accumulated experiences over times. This result is supported by Chhachhar, Chen and Jin [18] who ascertained that farmers experience is an important factor in mobile phone usage in India. Education was positive and statistically significant at l% each in Osun and Oyo States. This implies that education increases the likelihood of using agricultural smartphone apps in Southwest, Nigeria. Education plays an important roles in the sense that farmers who are educated are more likely to be exposed to new technology that will help them increase their farm productivity, hence influencing their decision to use agricultural smartphone apps. Residing in programme community was positive and significantly contributes to the decision to use agricultural smartphone apps in Oyo State. This implies that farmers who reside in communities where agricultural smartphone app sensitization and training programme have been conducted are more likely to use agricultural smartphone apps. This is because they are more informed about the usefulness of the agricultural smartphone apps in improving their farm productivity. Membership of association plays an important role in assisting farmers to source for useful information that will help them improve their farm productivity. Membership in association is positive and statistically significant at l% level of probability implying that it increases the likelihood of using agricultural smartphone apps in Osun State. This can be ascribed to the fact that farmers who are members of association enjoys group dynamics and thus having access to timely information that will be useful to them such as information on different available agricultural smartphone apps for their use. This result is corroborated by Asa and Uwem [8] who found that farmers' cooperative societies help spread the availability of mobile apps for farmers' use in Southwest, Nigeria.

Receiving training on the use and application of agricultural smartphone app was found to be positive and statistically significant at l0% in Osun State. This implies that receiving training on the use and application of agricultural smartphone apps increases the likelihood of using agricultural smartphone apps in Southwest, Nigeria. Furthermore, the fact that the agricultural smartphone apps are user friendly increases the likelihood of using them as it was found positive and statistically significant at 5% in Osun State. This implies that agricultural smartphone apps that are easy-to-use by the farmers are more likely to be use by the farmers in Southwest, Nigeria.

Implications of the use of agricultural smartphone apps on total factor productivity and technical efficiency of the farmers

We presented the parameter estimates of the cobb–douglas stochactic production models in Table 5. The result were presented separately for the treated, that is, the users of the agricultural smartphone apps and non-treated and control (non-users of the agricultural smarphone apps). In addition, the two models, pooled and true fixed effects were also presented showing similar results for the farm inputs prescribed by the apps. The inputs considered includes seed, fertilizer, labour and area of land. It should be noted that temperature, precipitation and other agroecological variables are controlled in the production function to estimate TFP. In Oyo State, the coefficient for the farm inputs of the treated group are all positive and statistically significant at l%. For the non-treated, the coefficients of the inputs were all positive while only seed and fertilizer was statistically significant at l%. For the control group, the coefficients of seed and area of land was statistically significant at l% while all the inputs were positive. In Osun State, the coefficients for the farm inputs of the treated group were all positive and statistcially significant at l% while for the non-treated group, all the coefficients of the inputs were positive although only the coefficients of fertilizer and labour was statistically significant. For the control group, all the coefficients of the inputs were positive while only the coeffieicnts of seed and area of land was statistically significant. Notably from our result, in Oyo State, the pooled result for the treated, non-tretaed and control groups indicates that maize seeds weigh more than the area of land on the output of maize, i.e., the partial elasticity of production is greater than maize area, fertilizer and labour. In addition, the partial elasticities of the three important inputs (i.e., seed, fertlizer and area of land) add up to 0.76, l.03 and 0.l7 for the treated, non-treated and control groups, respectively. Thus, seed rate (kg of seed per kg of fertilizer per ha) indicates an important inputs for maize production for all the groups. Similar result is otain on Osun State, for example, the pooled result for the treated, non treated and control groups shows that maize seed outweighs all other inputs. The partial elasticities of seed, fertilizer and area of land add up to l.0, l.3 and 0.58 for treated, non-treated and control groups, respectively. This results is similar to that of Adebayo et al. [2] who found an increased output of crops in Nigeria when cultivated with irrigation technology.

In measuring the economics of scale, for Oyo State, the addition of the partial elasticities for all the production inputs (seed, fertilizer, labour and area of land) for the two models (pooled and TFE) were 1.02 and 1.09 (treated), 1.042 and 0.62 (non-treated), 0.19 and 0.34 (control). This result suggest that the since the value for the treated in both models were greater than 1, then the treated group experience increasing returns to scale. This might be attributed to the influence of the use of agricultural smartphone apps. For the non-treated and control groups, one of the model in the non-treated shows a value less than 1 indicating decreasing returns to scale. Also for the control group, both models shows a value less than 1 which also indicates a decreasing returns to scale. In Osun State, on the other hand, the addition of the partial elasticities for all the production inputs (seed, fertilizer, labour and area of land) for the two models (pooled and TFE) were 1.18 and 1.3 (treated), 1.4 and 1.24 (non-treated), 0.6 and 0.92 (control). This reveals that the since the value for the treated in both models were greater than 1, then the treated group experience increasing returns to scale. This might also be attributed to the influence of the use of agricultural smartphone apps for farm inputs decision. For the non-treated, the two models shows a value greater than 1 indicating increasing returns to scale. This might be attributed to the spill-over effect of users of agricultural smartphone apps in these villages. Also for the control group, both models shows a value less than 1 which also indicates a decreasing returns to scale.

The coefficients of the constant term is statistically significant at 1% and positive in the pooled model for the treated, non-treated and control groups, while in the TFE model, the constant is suppressed in intervention and non-intervention communities for the treated, non-treated and control groups where the coefficients were statistically significant at 1%. The result also shows that

Table 5 Estimates of C-D stochastic production frontier for the pooled and true fixed effects of the users and non-users of agricultural smartphone apps

Stochastic production frontier (SPF)	Oyo						Osun					
	Pooled			True fixed effects (TFE)			Pooled			True fixed effects (TFE)		
	Treated	Non-treated	Control	Treated	Non-treated	Control	Treated	Non-treated	Control	Treated	Non-treated	Control
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
Seed	0.395*** (0.095)	0.780*** (0.149)	0.0689*** (0.0002)	0.299*** (0.004)	0.236*** (0.047)	0.221*** (0.059)	0.403*** (0.123)	0.514 (0.434)	0.403*** (0.123)	0.647*** (0.094)	0.420*** (0.078)	0.387*** (0.010)
Fertilizer	0.147*** (0.031)	0.236*** (0.047)	0.047 (0.031)	0.539*** (0.034)	0.229*** (0.059)	0.059*** (0.018)	0.237*** (0.081)	0.431*** (0.190)	0.0001 (0.0001)	0.233*** (0.067)	0.309*** (0.315)	0.138*** (0.009)
Labour	0.258*** (0.009)	0.011 (0.014)	0.0134 (0.011)	0.041*** (0.0024)	0.151 (0.168)	0.047 (0.031)	0.179*** (0.079)	0.293*** (0.003)	0.020 (0.220)	0.293*** (0.113)	0.387*** (0.018)	0.160* (0.125)
Land	0.216*** (0.007)	0.015 (0.014)	0.058*** (0.009)	0.213*** (0.043)	0.0008** (0.0004)	0.0l3 (0.011)	0.369*** (0.227)	0.169 (0.227)	0.179*** (0.079)	0.120* (0.024)	0.128 (0.109)	0.233*** (0.067)
Constant	0.236*** (0.047)	0.335*** (0.094)	0.064* (0.033)	Suppressed	Suppressed	Suppressed	0.693*** (0.116)	0.237*** (0.081)	1.652*** (0.484)	Suppressed	Suppressed	Suppressed
Intervention communities				0.247*** (0.094)	2.387*** (0.710)	5.320*** (0.678)				0.909*** (0.315)	2.387*** (0.710)	1.056*** (0.4l8)
Non-intervention communities				0.909*** (0.315)	0.738*** (0.239)	1.020***(0.324)				0.844*** (0.289)	0.179*** (0.079)	0.403*** (0.123)
$\sigma 2v$	0.229	0.319	0.462	0.472	0.219	0.713	0.511	0.281	0.599	0.381	0.711	0.227
$\sigma 2u$	0.738	0.472	0.028	0.487	0.872	0.333	0.292	0.311	0.377	0.552	0.836	0.371
$\lambda = \sigma u_{/\sigma v}$	0.237*** (0.081)	2.390*** (0.114)	5.553*** (0.756)	3.323** (1.716)	8.890*** (1.332)	2.401*** (0.986)	3.592*** (0.693)	2.067** (0.986)	4.147*** (l.39)	11.088*** (2.443)	2.391*** (0.l89)	1.173* (0.884)
N	65	85	60	65	85	60	50	70	50	50	70	50
Log likelihood												
AIC	189.7	184.5	187.2	178.6	179.3	179.5	196.4	195.1	196.9	192.3	193.7	192.5

See Figures in parenthesis are robust standard error

***,**, * represent statistical significant at l%, 5% and l0% level of probability

Table 6 Estimates of the total factor productivity index and technical efficiency of users and non-users of agricultural smartphone apps in Oyo State

Model	Treated				Non-treated				Control			
	Mean	Std. Dev	Max	Min	Mean	Std. Dev	Max	Min	Mean	Std. Dev	Max	Min
TFPI												
Pooled	0.617	0.169	1.00	0.057	0.526	0.154	1.00	0.062	0.558	0.163	l.00	0.042
True Fixed Effects (TFE)	0.689	0.174	1.00	0.061	0.539	0.161	1.00	0.068	0.562	0.152	l.00	0.046
F-test	0.0923*** (0.0252)											
Technical Efficiency (TE)												
Pooled	0.746	0.166	0.933	0.429	0.633	0.182	0.912	0.310	0.67 l	0.172	0.911	0.5l9
True Fixed Effects (TFE)	0.782	0.167	0.937	0.467	0.647	0.177	0.924	0.332	0.683	0.184	0.927	0.526
F-test	0.9092*** (0.3150)											

*** represent significance at 1%

NB: TFPI and TE calculations are based on C-D SPF estimates

the AIC vales estimated for the alternative model specification in Oyo state are 189.7, 184.5 and 187.2 for the treated, non-treated and control group, respectively, for pooled model while the value for TFE model for the treated, non-treated and control groups were 178.6, 179.3 and 179.5, respectively. In Osun State, the AIC values of the pooled model for the treated, non-treated and control groups were 196.4, 195.1 and 196.9, respectively, while the values of the TFE model were 192.3, 193.7 and 192.5 for the treated, non-treated and control groups, respectively. Thus, the TFE model is the most preferred model over the pooled specification.

We summarized and presented the result of the TFPI and TE in Tables 6 and 7. The result for Oyo State is presented in Table 6. The result were disaggregated into treated, non-treated and control groups. It should be noted that temperature, precipitation and other agro-ecological variables are controlled in the production function to estimate TFP. From Table 6, the mean TFPI for the treated is 0.6l7 (pooled) and 0.689 (TFE) with min–max range of 0.57–l.00. The mean TFPI for the non-treated is 0.526 (pooled) and 0.539 (TFE) with min–max range of 0.062–l.00 while the mean TFPI for the control is 0.558(pooled) and 0.562(TFE) with min–max range of 0.042–l.00. These figures imply that the TFPI of the users of agricultural smartphone apps (treated) are higher than that of the non-users (treated and control group) indicating that the users have higher productivity margin than the non-users. This may be attributed to the impact of the agricultural smartphone apps being used by the treated farmers since temperature, precipitation and other agro-ecological variables are controlled in the production function to estimate TFP. It should also be noted from the result in Table 6 that the TFPI of the non-treated is higher than that of the control group implying that the non-treated group have higher productivity margin than the control group. This may be due to the spill-over effect of the use of agricultural smartphone apps by the treated farmers since they reside in the same community with the non-treated, thus, they might have been obtaining

Table 7 Estimates of the total factor productivity index and technical efficiency of users and non-users of agricultural smartphone apps in Osun State

Model	Treated				Non-treated				Control			
	Mean	Std. Dev	Max	Min	Mean	Std. Dev	Max	Min	Mean	Std. Dev	Max	Min
TFPI												
Pooled	0.663	0.152	1.00	0.052	0.437	0.171	1.00	0.062	0.502	0.159	1.00	0.041
True Fixed Effects (TFE)	0.694	0.193	1.00	0.058	0.464	0.162	1.00	0.067	0.528	0.177	1.00	0.043
F-test	0.539*** (0.034)											
Technical Efficiency (TE)												
Pooled	0.826	0.173	0.937	0.391	0.649	0.155	0.936	0.4l9	0.631	0.166	0.942	0.362
True Fixed Effects (TFE)	0.875	0.158	0.952	0.382	0.673	0.149	0.942	0.426	0.652	0.169	0.947	0.368
F-test	0.420***(0.078)											

*** represent significance at 1%

NB: TFPI and TE calculations are based on C-D SPF estimates useful production information on quantity of inputs to be used to achieve higher productivity from their friends who are already using the agricultural smartphone apps. We further conducted an F-test of the mean of TFPI and TE for the three categories which was found significant. This implies that users (treated) of agricultural smartphones had higher TFPI and TE than non-users (non-treated and control) in Oyo State subsample.

In Osun State, on the other hand, the summarized result presented in Table 7 indicates that the mean TFPI of the treated is 0.663 (pooled) and 0.694 (TFE) with min–max range of 0.052–1.00. The mean TFPI of the non-treated is 0.437 (pooled) and 0.464 (TFE) with min–max range of 0.062–1.00 while the mean TFPI of the control is 0.502 (pooled) and 0.528 (TFE) with min–max range of 0.041–1.00. This result shows that the TFPI of the treated (users of agricultural smartphone apps) is higher than the non-treated and control (non-users) with non-treated being higher than the control group also. This implies that the users of agricultural smartphone apps have higher productivity margin than the non-users of agricultural smartphone apps. Likewise, we conducted an F-test of the mean of TFPI and TE for the three categories in Osun State subsample which was found significant. This also implies that users (treated) of agricultural smartphones had higher TFPI and TE than non-users (non-treated and control).

These results are consistent with the findings of Baumüller [14], Kante et al. [39], Kirui et al. [42], and Wyche & Steinfield [86] who all find an increased farm level productivity as a result of the use of mobile apps for agricultural production in Kenya and Nigeria.

With respect to the technical efficiency (TE) result, in Oyo State, the TE result presented in Table 6 shows that the mean TE of the treated is 0.746 (pooled) and 0.782 (TFE) with min–max range of 0.429–0.937. The mean TE of non-treated is 0.633 (pooled) and 0.647 (TFE) with min–max range of 0.310–0.924 while the mean TE of the control is 0.671 (pooled) and 0.683 (TFE) with a min–max range of 0.519–0.927. This result shows that the users of agricultural smartphone apps (treated) have higher TE values than the non-user of agricultural smartphone apps (non-treated and control). This implies that users of agricultural smartphone apps are more technically efficient than the non-users. This may be attributed to the important information being suggested by the agricultural smartphone apps on the quality and quantity of production inputs to be combined for production of maize among the treated farmers. In Osun State, on the other hand, the mean TE of the treated is 0.826 (pooled) and 0.875 (TFE) with min–max range of 0.391–0.952 (Table 7). The mean TE of the non-treated is 0.649 (pooled) and 0.673 (TFE) with min–max range of 0.419–0.942 while the mean TE of the control group is 0.631 (pooled) and 0.652 (TFE) with a min–max range of 0.362–0.947. This findings also shows that the mean TE of the users of agricultural smartphone apps (treated) is higher than that of the non-users (non-treated and control) implying that the users of agricultural smartphone apps have higher farm productivity level than the non-users of agricultural smartphone apps. These findings agrees with similar findings of Qiang et al. [75] and Baumüller [15] who all reported a higher farm productivity level for users of agricultural smartphone apps in Tanzania and Kenya. In addition, the intervention community fixed effects model used in this study accounted for the unobservables, thus affecting productivity values. Therefore, the most preferred model in this study is the TFE model because it controlled for unobserved heterogeneity of the use of agricultural smartphone apps among the maize farmers. This TFE model generates a relatively higher TFPI and TE estimates when compared with the pooled model, thus its preferences.

Conclusions

In this study, we examine the effect of exposure to agricultural smartphone apps on the adoption and use of agricultural smartphone apps among smallholder farmers in Southwest, Nigeria while also assessing the effects of the use of agricultural smartphone apps on total factor productivity and technical efficiency of the farmers. Through this study, we found that exposure to agricultural smartphone apps has a higher chances of increasing the use of agricultural smartphone apps across farmers populations in Southwest, Nigeria. Results from this study shows the importance of increasing adoption rate of agricultural smartphone apps through awareness creation and training of farmers on new technology such as agricultural smartphone apps while intimating the farmers on the benefits they are to accrue as a result of the use of the agricultural smartphone apps in improving their farm productivity. Findings from this study also implies that the use of agricultural smartphone apps increase farm level productivity since users of agricultural smartphone apps have higher total factor productivity and were more technically efficient than non-users of the agricultural smartphone apps in Southwest, Nigeria.

Policy implications

The result of this study implies that policy makers, private agencies, government organizations and app developers need to intensify their awareness creation efforts so as to sustain the current use of the agricultural smartphone apps while increasing their efforts to reach out to more farmers. This sensitization and training efforts will no doubt increase the adoption rate of the different agricultural smartphone apps among the farmers. Furthermore, strengthening the extension services capacity in Nigeria will go a long way in providing technical support and useful information to the farmers about the agricultural smartphone apps which will subsequently increase the adoption rate of the available agricultural smartphone apps among the farmers. The agricultural smartphone apps developers are also encouraged to make the apps user-friendly and easy to operate as this will encourage the farmers to easily download and install the apps on their smartphone. Network operators in Nigeria should also ensure that network coverage assess improve especially in rural villages in Nigeria where the bulk of the smallholder farmers resides and practices agricultural production. Smallholder farmers are also encourage to join farmers organizations where they will have access to timely and up-to-date information about latest technology such as agricultural smartphone apps.

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