

Research article

A tobit regression model for the timing of smartphone adoption in agriculture

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HIGHLIGHTS

- Tobit regression model for the timing of smartphone adoption in German agriculture.
- Analysis allows the identification of early and late adopters.
- Farmers' age, risk attitude and farm location influence the adoption timing.
- Results are of interest for agricultural policy makers and extension services.

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ABSTRACT

Smartphones are excellent tools well-suited for applications in agriculture because of their mobility, high data processing power, access to agricultural apps, and compatibility with precision agriculture technologies. Although smartphone adoption and the use of agricultural apps are well-studied, variables influencing the timing of smartphone adoption in agriculture have not yet been closely examined. Comprehending both the timing of when a certain technology is adopted and identifying the specific characteristics of early and late adopters aids in the anticipation and thereby the fostering of the diffusion process. This study's objective is therefore to analyse the timing of smartphone adoption for agricultural purposes by applying a tobit regression model to a data set of 207 German farmers, which was collected in 2019. The results indicate that significant factors influencing the timing of smartphone adoption in agriculture include farmers' gender, risk attitude, age, size and location of their farm, among other factors. These results may be interesting to several stakeholders in agriculture such as extension services, policymakers and researchers as well as smartphone providers and sellers.

1. Introduction

Information and communication technologies (ICT) are an important driver of agricultural production globally. ICT has the potential to benefit agricultural production management, production chains, and marketing of agricultural products. ICT can also facilitate efficient use of natural resources in agriculture and improve food access and food security (Parlasca et al., 2020; Aker et al., 2016; Mendes et al., 2020; Luboslav et al., 2017). Smartphone technology is a fundamental, rapidly evolving sector of ICT. Smartphones are multipurpose tools with a high computing capacity, built-in sensors and mobile internet access. They are flexible in their functionality through downloading of software in the form of applications (Teacher et al., 2013; Hübler and Hartje 2016). Because of advances in technology such as the independence of landline data

networks, Hübler and Hartje (2016) propose that smartphones play a key role in the development of rural economies and technology. For this reason, Hübler and Hartje (2016) argue that policymakers should support the diffusion of smartphones in rural communities.

The core of rural communities and economies in both developing and developed countries is still represented mainly by farmers (Jeffcoat et al., 2012). Smartphones stand to benefit rural regions both by increasing interconnectivity through mobile internet and by bolstering agricultural businesses (Michels et al., 2020c). It is highlighted by Landmann et al. (2020) that smartphones enhance the organisational and decision-making capabilities of farmers through access to up-to-date, accurate information, enabling farmers to make informed and timely choices in their business and crop management. Additionally, smartphones blend well into the daily working routine of farmers because of

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their built-in sensors, ability to download tools such as agricultural apps, and mobile internet access¹ (Pongnumkul et al., 2015; Bonke et al., 2018). Decision support tools (DST) often take form as agricultural apps, for example, in the area of plant protection (Bonke et al., 2018; Michels et al., 2020a) or dairy herd management (Michels et al., 2019a), where some farmers already benefit from these apps. Moreover, the integration of smartphones with on-farm sensors and precision agriculture technologies (PAT) (Vellidis et al., 2016; Michels et al., 2020b) can be used in the facilitation and mediation of data collection and analysis (Fulton and Port 2018). In this context, the use of smartphones can contribute to animal welfare as well as to the reduction of negative externalities in the context of agricultural production by improving farmers decision making. For instance, Ma and Zheng (2021) provide evidence providing information via smartphones can help to increase the efficient use of pesticides and fertilizers.

In respect to developing countries specifically, smartphone use is increasing (Baumüller 2017; Nakasone and Torero 2016). Smartphones serve as a valuable access point to financial services and information via mobile internet. Particularly in terms of internet access, farmers in remote areas without landline internet stand to benefit greatly from smartphone access (Aker et al., 2016). In remote regions, DST in the form of apps play an important role since they provide access to information from agricultural extension services while specifically tailoring information to the farm site (Oyinbo et al., 2020). Therefore, smartphones are a key instrument in disseminating knowledge to improve on-farm decision making and providing access to several stakeholders regardless of a farmer's country setting. Apps allow for specific tailoring of functions and information depending on farmers' needs and location. In this way, smartphone usage can contribute to the sustainable development of agriculture globally.

Yet, there are only a few publications covering the adoption and use of smartphones in agriculture. Although farmers' decision-making regarding smartphone adoption (Michels et al., 2020b) and their usage of agricultural apps (Michels and Musshoff 2020) have been topics of prior research, this is the first study to investigate the timing of smartphone adoption. A farmer's decision to apply smartphone technology early on or delay its adoption is important as it brings certain (dis)advantages. For example, farmers who embrace smartphone adoption earlier may benefit from the new technology but face obstacles in implementation or due to immature app development. Farmers who adopt smartphones later may benefit from more developed technology at a lower cost, but do not stand to benefit as much as early adopters from implementing this new technology.

The adoption and diffusion of new agricultural technologies is considered a gradual process (Jaffe et al., 2002), which is dependent on characteristics of the farmer and farm site (Fuglie and Kascak 2001). Along these lines, Watcharaanantapong et al. (2014) demonstrated that certain traits of farmers and farm sites affect the timing of PAT adoption. Therefore, this study aims to identify farm characteristics and the role of farmers in regard to their timing of smartphone adoption. For this purpose, the classification of factors affecting PAT by Pierpaoli et al. (2013) (socio-demographic variables, financial resources related variables and competitive and contingent variables) is applied for the timing of smartphone adoption in agriculture.

In order to anticipate the diffusion of smartphones among farmers, it is crucial to understand the timing of adoption by identifying early adopters. This information aids in fostering the adoption process for those who delay it. Furthermore, it allows for more targeted and precise marketing for providers and sellers of smartphones and agricultural technology, including but not limited to apps. Along these lines, information about early adopters, specifically the obstacles or challenges of agricultural smartphone use, could be analysed and implemented to

remove these barriers and facilitate smartphone use. Consequently, understanding the timing of the adoption process and factors affecting the adoption decision is important to reduce the adoption lag among the farmers through the development of educational programs tailored to farmers' preferences and barriers. Finally, this information can be used to facilitate the adoption and diffusion of smartphones by several stakeholders, including farmers and policy makers.²

The article makes the following contributions to literature: To the best of our knowledge, this will be the first study to examine the timing of smartphone adoption for agricultural purposes. Specifically, this study identifies characteristics of farmers and farms that adopt smartphone technology earlier versus those farmers who delay adoption. Furthermore, this study quantifies the timing difference in years with respect to the corresponding variables. In general, this paper contributes to the understanding of technology adoption and diffusion in agriculture by adding a new aspect dealing with the timing of smartphone adoption. Timing of adoption is analysed using a left-censored tobit regression model applied to a data set of 207 German farmers collected via an online survey in the first quarter of 2019.

2. Hypotheses generation

Innovation can be defined as an idea or object that is perceived as new by an individual (Rogers, 2010). In addition, Feder and Umali (1993) defined innovation as a technological factor which influences or changes the production function, which corresponds to Rogers' (2010) definition that adoption of an innovation means that something is done differently as before. Furthermore, Rogers (2010) argued that individuals are heterogenous and that their different characteristics affect the temporal stage of technology adoption. Specifically, people who adopt an innovation at an earlier temporal stage have different characteristics and sociodemographic traits than individuals who adopt an innovation later. Additionally, it has been shown that early adopter characteristics are not the same across all categories of innovation but rather vary with the empirical setting (Dedehayir et al., 2017). Unsurprisingly, numerous studies on the adoption of new technologies or innovations have also been published in the agricultural context which underline the importance of understanding farmers' adoption process (Dimara and Skruas, 2003). The adoption of new technologies or innovations is an important factor for agricultural productivity and farmers' economic and personal welfare (Chavas and Nauges, 2020). Moreover, the adoption of agricultural innovation is linked to food security and poverty reduction in the long run (de Janvry and Sadoulet, 2001). In a seminal survey paper by Feder et al. (1985) over 70 studies regarding the adoption of innovation in agriculture have been reviewed. Likewise, recent review papers deal with several publications investigating agricultural technology adoption in different contexts further displaying the currency of the topic (e. g. Takahashi et al., 2020; Pathak et al., 2019; Tey and Brindal, 2021). Hence, understanding technology adoption remains a central aspect for policy makers and researchers alike (Ogundari and Bolarinwa, 2018).

At the micro level, each decision unit (farmer, household) must decide to adopt a new technology or innovation (Feder and Umali, 1985). The adoption itself is a complex process which is influenced by a large set of factors (Feder and Umali, 1985; Dimara and Skruas, 2003; Dedehayir et al., 2017). Hence, it can also be expected that the timing of smartphone adoption in agriculture is influenced by several farm and farmers' related factors. Smartphones are unique multifunctional devices that incorporate the technologies of mobile phones, computers and PAT (Pongnumkul

¹ An overview of smartphone applications targeted to (precision) agriculture is available in Mendes et al. (2020) and Michels and Musshoff (2020).

² In advanced economies the Pew Research Center (2019) reports a median of smartphone ownership of 76% and for emerging economies of 45%. It can be assumed that the share of smartphone owners in rural communities, especially among farmers, is much smaller since innovations, especially in ICT, reach rural region at a later stage (Salemink et al. 2017). Especially, digitalisation in agricultural lags behind other sectors (Xin et al. 2015).

et al., 2015) and are also capable of integrating well with PAT (Michels et al., 2020b). To explicitly account for their suitability for precision agriculture purposes and relation to PAT, the classification of factors affecting the adoption of PAT by Pierpaoli et al. (2013) is adopted. Based on that classification, the considered farmers and farm characteristics are subdivided in socio-demographic variables (H1, H2, H3, H4, H5), financial resources related variables (H6, H7, H8) as well as competitive and contingent variables (H9, H10, H11, H12), which have the greatest likelihood of affecting the timing of smartphone adoption.

Michels et al. (2020b) demonstrated that the age of a farmer is negatively correlated with their smartphone use. Among many reasons, they found that older farmers have a lower digital literacy level in working with ICTs. This reasoning was also put forward by Rose et al. (2016) since younger farmers have been accustomed to digital technologies from a young age. This is tested in the following hypothesis:

H1. A higher farmers' age delays the timing of smartphone adoption (*Age*).

University-educated farmers are expected to have a higher level of technological competency (Paustian and Theuvsen 2017). Moreover, Carrer et al. (2017) stated that farmers with a university degree are also more information-seeking. Along these lines, Michels et al. (2020b) proposed that higher-educated farmers are more likely to be smartphone users as they favour smartphones for information retrieval. Considering these points, the following hypothesis will be tested:

H2. Holding a university degree fosters the timing of smartphone adoption (*Education*).

It is proposed by Doss and Morris (2000) that female farmers are less apt to embrace emerging technologies. Regarding smartphones, Michels et al. (2020b) demonstrated that gender does not play a role in smartphone ownership. However, regarding the intensity of smartphone usage, Michels and Musshoff (2020) showed that agricultural apps are more commonly used by male farmers. Although literature contains mixed results, it is hypothesized that male farmers are earlier adopters of smartphone technology than their female counterparts, as shown:

H3. Being a male farmer fosters the timing of smartphone adoption (*Gender*).

According to Taylor and Todd (1995) having prior experience with an information technology facilitates the uptake of a similar or advanced technology. In the agricultural context, several studies show that computer literacy correlates with an earlier adoption of PAT (Daberkow and McBride 2003; Paxton et al. 2011; Tey and Brindal 2012) given that technology-savvy farmers already possess the digital fluency required to apply PAT. According to Wang et al. (2014) modern smartphones resemble laptops by having comparable computational capability and internet access. Hence, farmers who are technologically fluent in laptop use easily embrace smartphones and therefore adopt them earlier than farmers without computer literacy.³ Therefore, the following is hypothesized:

H4. Having a laptop or PC fosters the timing of smartphone adoption (*Laptop, PC*).

A farmer's risk perception is an important characteristic in the decision regarding smartphone adoption (Feder 1980). New technologies may be risky to farmers in that the investment does not pay off (Baumgart-Getz et al. 2012). Similarly, newer technologies such as business-related smartphone functions may pose the risk of not yet being fully developed. Farmers who adopt these technologies early are more likely to be risk-seeking, and their late-adopting counterparts tend to be risk-averse (Rogers, 2010). Along these lines, earlier adopters of smartphones may be more likely to be risk-takers by nature. Therefore, the following is hypothesized:

H5. A less risk-averse attitude fosters the timing of smartphone adoption (*RiskAtt*).

Contract workers in agriculture provide various operational services to farmers, for example, harvest or fertilization (Michels et al., 2019b). Considering to their complex workload and contact with multiple customers in addition to their own farm site, a smartphone gives farmers many advantages over a regular mobile phone. Therefore, this study anticipates that farmers who perform contract work in addition to their own farm are more likely to be earlier adopters of smartphones. This is stated in the following hypothesis:

H6. Being an agricultural contractor fosters the timing of smartphone adoption (*Contractor*).

Part-time farmers who have competition for their time from an off-farm job could be considered to be less involved than a full-time farmer, who is fully concentrated on their farm business (Batte, 2005). In the context of precision agriculture, Daberkow and McBride (2003) show that part-time farmers are less likely to be aware of and thereby implement PAT on-farm. They reason their findings that farmers who are more dependent on farming have greater interest to become familiar with new technologies. In the same vein, full-time farmers may search more widely for any opportunity that would improve their farm operation and business. Since smartphones are tools that may support farmers in various farm and business-related tasks, such as access to agriculture-related news and price changes (Hoffmann et al. 2013), the following is hypothesized:

H7. Being a full-time farmer has a positive effect on the timing of adoption (*FullTime*).

Given the nature of their job, farm managers are responsible for all farm-related decisions. In order to make better-informed on-farm decisions, farm managers are more likely to consider agricultural apps and smartphones as DST and adopt them earlier than other agricultural workers. This relationship is shown in the following hypothesis:

H8. Being the farm manager fosters the timing of smartphone adoption (*Position*).

Social factors play an important role in farmers' decision to adopt smartphones (Ramirez, 2013). Some farms host agriculture apprentices, who are generally interested in new agricultural technologies. Therefore, farmers who frequently interact with interns and trainees are more likely to be exposed to and consider adopting smartphones for agriculture-related purposes. This relationship is displayed in the following hypothesis:

H9. A farm serving as a training location for agricultural apprentices fosters the timing of smartphone adoption (*Apprentice*).

Regarding the number of agricultural apps used, Michels and Musshoff (2020) demonstrated that organic farmers use smartphones less intensively than conventional farmers. Their logic follows that most agriculture apps available are developed for conventional farms. Therefore, we hypothesize that conventional farmers adopt smartphones earlier than organic farmers, as stated:

H10. Managing a conventional farm fosters the timing of smartphone adoption (*Conv*).

The high investment cost required for PAT is considered in literature to be a contributing factor to the correlation between PAT use and farm size (Tey and Brindal 2012). In comparison to PAT, smartphones are inexpensive (Pongnumkul et al. 2015), however, Michels et al. (2020b) still points to a positive correlation between smartphone adoption and farm size. This may be due to smartphones' multifunctionality for organizational purposes, which larger farms rely on more than smaller farms. Therefore, the following is hypothesized:

H11. A higher farm size in hectares arable land fosters the timing of smartphone adoption (*FarmSize*).

A farm's location impacts farmers' access to mobile internet coverage (Hennessy et al. 2016). Adequate mobile internet access is essential for

³ The term "computer literacy" refers to the ability to use computers, laptops and related technologies efficiently.

full smartphone functionality. Along these lines, Michels et al. (2020b) show that farmers living in the southern Federal states of Germany are less likely to adopt smartphones in comparison to the rest of the country, since LTE net coverage is less developed in southern than northern Germany. For this reason, the timing of smartphone adoption is likely also affected by a farm’s geographic location, as stated in the hypothesis below:

H12. Farms located in southern Germany have delayed smartphone adoption due to reduced mobile internet coverage (*Region*).

3. Material and methods

3.1. Survey design and data collection

German farmers were invited to partake in an online survey in the first quarter of 2019. The survey was programmed using the unipark software (unipark, 2021). In a previous study, Michels et al. (2019b) provided empirical evidence based on a representative sample, that over 95 % of the German farmers used the internet in 2016; three out of four farmers on a daily basis. Hence, it was expected to reach a relatively unbiased sample of the German farmer population even if we use an online survey. For this reason, the survey was distributed online via social media and agriculture-centred online forums and newsletters. The invitation was posted once, and no subsequent invitations were sent or posted. Furthermore, a requirement for participation in the survey was that farmers needed to be active in arable farming. Consequently, using the internet to acquire the participants non-probability sampling is used.

Prior to starting the survey, farmers were notified that they could end their participation in the study at any time. They were also informed that the evaluation of the survey is absolutely anonymous and that no conclusions can be drawn about individuals on the basis of the results. In this two-part survey, farmers first entered information on characteristics regarding socio-demographic and farm-related information, as explained in the hypotheses generation section. Second, farmers answered to whether they used various digital technologies including smartphones, mobile phones and laptops. They also recorded how long they used these technologies for agricultural purposes, which serves as the dependent variable in the analysis. The results section contains these collected variables and their descriptive statistics.

3.2. Conceptual and theoretical framework

The time-to-adoption decision has been investigated in agriculture using duration analysis in several contexts like organic agriculture or conservation tillage (e. g. Burton et al. 2003; D’Emden et al. 2006). Likewise, non-parametric duration analysis has also been applied to study the timing of PAT adoption (Ofori et al. 2020). In the study by Ofori et al. (2020) the difference between the year of adoption and the year that a technology becomes commercially available was used as a dependent variable. While it may initially seem conceivable to apply the same (econometric) technique for the investigation of smartphone adoption timing, one must consider remarkable differences between smartphones and precision agriculture technologies in this context. First of all, smartphone technology has evolved over time from PDAs and mobile phones. Thus, it is more difficult to provide an exact date for the commercial availability of smartphones. Second, the focus of this study lies in the general use of smartphones for agricultural purposes and not in the use of a specific agricultural smartphone service or app. Hence, it is even harder to name an exact date of commercial availability. We therefore applied an alternative conceptual and theoretical framework derived from Watcharaanantapong et al. (2014) which will be explained in the following.

A farmer *i* is confronted with the choice whether or not to adopt a smartphone *Sm*. The expected utility from smartphone adoption *Ad* is $E[U_{Ad}(\pi_{ism}^{Ad})]$ and the expected utility from non-adoption *NAd* is

$E[U_{NAd}(\pi_{ism}^{NAd})]$. π_{ism}^{Ad} and π_{ism}^{NAd} are the benefits with and without smartphone adoption and use for agricultural purposes, respectively. Defining

$$U_{ism}^* = E[U_{Ad}(\pi_{ism}^{Ad})] - E[U_{NAd}(\pi_{ism}^{NAd})] \tag{1}$$

a farmer will adopt the smartphone *Sm* for agricultural purposes if $U_{ism}^* > 0$.

This lies under the assumption that this survey took place during year t_s and farmer *i* declared to have adopted a smartphone in year t_a . Hence, the smartphone experience of farmer *i* in years (*SmExp_i*) as a measure for the timing of adoption can be estimated as follows:

$$SmExp_i = t_s - t_a \tag{2}$$

Under the condition that farmer *i* has not adopted a smartphone before t_s , thereby not reporting a year of adoption t_a , then $SmExp_i = 0$. If a farmer *i* adopted a smartphone in year t_a before t_s then $SmExp_i > 0$. An earlier adoption timing is signified by a larger value of *SmExp* due to the great difference between the time of smartphone adoption and the time the survey was conducted.

For a tobit model it is assumed that the dependent variable Y_j for the observations $j = 1, \dots, n$ satisfy (Wooldridge, 2013; Greene, 2018):

$$Y_j = \max(Y_j^*, 0) \tag{3}$$

which means that *Y* is observed for values greater than 0 but not values of 0 or less. Considering these points, the best model for estimating German farmers’ adoption of smartphones would be a tobit model (Tobin, 1958). Specifically, this tobit regression model can be defined as follows⁴ (Wooldridge, 2013; Greene, 2018):

$$SmExp_i^* = x_i'\beta + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2)$$

$$SmExp_i = \begin{cases} SmExp_i^* & \text{if } SmExp_i^* > 0 \\ 0 & \text{if } SmExp_i^* \leq 0 \end{cases} \tag{4}$$

where $SmExp_i^*$ is a latent variable, which can be observed if, and only if, the values are greater than 0. β is the vector of explanatory variables x_i (e.g. farmer and farm characteristics) and ε_i is a normally distributed error term. The log-likelihood function to be maximized to estimate β and σ can be written as follows (Wooldridge, 2013; Greene, 2018):

$$\max_{\beta, \sigma} \ln L = \sum_{SmExp_i > 0} \ln \left[\frac{1}{\sigma} \varphi \left(\frac{SmExp_i - x_i'\beta}{\sigma} \right) \right] + \sum_{SmExp_i = 0} \ln \left[1 - \Phi \left(\frac{x_i'\beta}{\sigma} \right) \right] \tag{5}$$

where Φ is the cumulative distribution function of a standard normal distribution, and φ is the matching density function. Marginal effects⁵ of an explanatory variable β_k on the expected value (*E*) for *SmExp_i* can be estimated as follows (Wooldridge, 2013; Greene, 2018):

$$\frac{\partial E[SmExp_i]}{\partial x_{i,k}} = \beta_k \Phi \left(\frac{x_i'\beta}{\sigma} \right) \tag{6}$$

Following the conceptual and theoretical considerations, the following empirical model is to be estimated:

⁴ The timing of this survey in early 2019 decreased the likelihood that farmers would answer as having adopted smartphones in this same year, thereby resulting in $SmExp_i = 0$ as per Eq. (2) and be therefore censored in the tobit regression estimation according to Eq. (4).

⁵ In these tobit models, three potential marginal effects must be estimated. The dependent variable’s marginal effect on the expected value is estimated based on guidelines from Wooldridge (2013) and Greene (2018).

$$\begin{aligned}
 SmExp_i = & \beta_0 + \beta_1 Age + \beta_2 Education + \beta_3 Gender + \beta_{4a} Laptop + \beta_{4b} PC \\
 & + \beta_5 RiskAtt + \beta_6 Contractor + \beta_7 FullTime + \beta_8 Position + \beta_9 Apprentice \\
 & + \beta_{10} Conv + \beta_{11} FarmSize + \beta_{12} Region + \epsilon_i
 \end{aligned}
 \tag{7}$$

where $SmExp_i$ is the number of years a farmer i uses a smartphone for agricultural purposes in 2019 (t_s) when the survey was conducted. $SmExp_i$ is specified as a function of farmer and farm characteristics.

Biased standard errors can occur through multicollinearity when two or more explanatory variables are correlated (Mansfield and Helms 1982). Variance inflation factors (VIFs) are estimated to identify potential occurrences of multicollinearity, which should not be higher than 5 (Curto and Pinto 2011). Hence, VIFs were estimated prior to the tobit model. Furthermore, the tobit model assumes normally distributed residuals (Holden, 2004) to ensure the validity of p-values for t-tests. Several estimates are made to ensure that this condition is satisfied, including a standardized normal probability plot (P-P), a kernel density plot, the inter-quartile range, a plot of the quantiles, as well as a Shapiro-Wilk W test. The estimation was carried out using STATA 14.2 with robust standard errors to account for heteroscedasticity.

4. Results and discussion

4.1. Descriptive results

Of the collected surveys, 207 remained after removal of unfinished surveys. This satisfies the least sample size estimation based on Bartlett et al. (2001) with a population size of 266,660 German farms (Statista, 2019) and an applied confidence interval of 99 % and an applied margin of error of 10 %. The explanatory statistics regarding smartphone usage and ownership are displayed in Table 1. Also included in Table 1 and Figure 1 are the sociodemographic variables (H1-H5) and financial resource-related variables (H6-H8), which were part of the econometric analysis. In this sample, 95% of farmers own smartphones, far exceeding the German average of 62 % (AgriDirect Deutschland GmbH, 2016). The average length of smartphone use in this sample was 7.62 years. The average age of farmers in the sample is 39 years (H1) was below the German national average of 53 years (H1). Over half of the farmers in the sample were university-educated at 52% (H2), which does not correspond to the

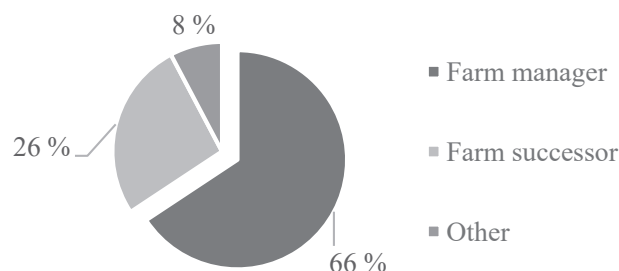


Figure 1. H8 (Position): Farmers' position on the farm (N = 207). H = Hypothesis.

national average of 12%. Regarding gender, 6 % of farmers were female (H3), in comparison to the German national average of 10 % (German Farmers Federation, 2020). In terms of digital technology, 66% of farmers possess laptops and 79% state they have a PC (H4). An 11-point scale from (Dohmen et al. 2011) was used to determine risk attitude. A risk-neutral individual would be ranked a 5 on this 0 - 10 scale, risk-averse individuals rank a 4 or below, and risk-seeking individuals rank a 6 or higher. Farmers in this sample were considered to be risk-neutral on average with a value of 5.42 (H5). In the sample, few farmers (27%) perform contract work in addition to their own farms (H6). 90% of surveyed farmers worked full-time (H7) in contrast to the German national average of 48% (German Farmers Federation, 2020). Descriptive results regarding the variable Position (H8) can be seen in Figure 1. Regarding position, 66 % of sampled farmers were the manager, 27% were farm successors, and 8% were other relatives or employees (labelled “Other” in Figure 1”).

Table 2 and Figure 2 summarize results of the contingent and competitive variables (H9 – H12). Most farms (66 %) hosted agricultural trainees (H9). Additionally, 85% of sampled farmers were conventional (H10), similar to the German national average (89%). The average size of farms in the sample (H11) surpasses the German average at 298 ha of arable land in comparison to 65 ha Figure 2 displays descriptive results of Region (H12). The majority of farms surveyed are found in the north of Germany (37 %) succeeded by the south (31 %) and the west (20 %), with the least farms in the sample located in east Germany (12 %). This sample is not representative of the German national average (German Farmers Federation, 2020).

Table 1. Descriptive statistics for the use of smartphones as well as sociodemographic and financial resource-related variables (N = 207).

H	Variable	Description	Mean	SD	Min	Max	German average ^c
	<i>Smartphone</i>	1, if the farmer has a smartphone for agricultural purposes; 0 if not	0.95	-	0	1	0.62
	<i>SmExp</i> ^a	Smartphone experience in years	7.62	2.47	1 ^d	11	n. a.
Socio-demographic variables							
H1	<i>Age</i>	Farmers' age in years	39.13	11.90	19	67	53
H2	<i>Education</i> ^c	1, if the farmer has a university degree; 0, if not	0.52	-	0	1	0.12
H3	<i>Gender</i> ^c	1, if the farmer is male; 0, if not	0.94	-	0	1	0.90
H4	<i>Laptop</i> ^c	1, if the farmer uses a laptop; 0, if not	0.66	-	0	1	n. a.
	<i>PC</i> ^c	1, if the farmer uses a PC; 0, if not	0.79	-	0	1	n. a.
H5	<i>RiskAtt</i> ^b	Farmers' risk attitude	5.42	1.75	1	10	n. a.
Financial resources related variables							
H6	<i>Contractor</i> ^c	1, if the farmer is an agricultural contractor; 0, if not	0.27	-	0	1	n. a.
H7	<i>FullTime</i> ^c	1, if the farmer is a full-time farmer; 0, if not	0.90	-	0	1	0.48

SD = Standard deviation, H = Hypothesis.

^aDependent variable, Mean and standard deviation shown for *Smartphone* = 1 (N = 198).

^bRisk attitude measure on the scale developed by Dohmen et al. (2011) with 0 – 4 = risk-averse, 5 = risk-neutral, 6 – 10 = risk-seeking.

^cGerman Farmers Federation (2020) and AgriDirect Deutschland GmbH, 2016

^dNo farmers reported new, agriculture-related use of a smartphone in early 2019.

^eThe mean of a dummy variable shows the share among the sample.

Table 2. Descriptive statistics for the competitive and contingent variables (N = 207).

H	Variable	Description	Mean	SD	Min	Max	German average ^a
Competitive and contingent variables							
H9	Apprentice ^b	1, if the farm is a training location for agricultural apprentices 0, otherwise	0.66	-	0	1	n. a.
H10	Conv ^b	1, if the farm is farmed conventionally; 0, otherwise	0.85	-	0	1	0.89
H11	FarmSize	Farm size in hectares of arable land	297.90	486.67	4	3,800	65

SD = Standard deviation, H = Hypothesis.

^aGerman Farmers' Federation (2020)

^bThe mean of a dummy variable shows the share among the sample.

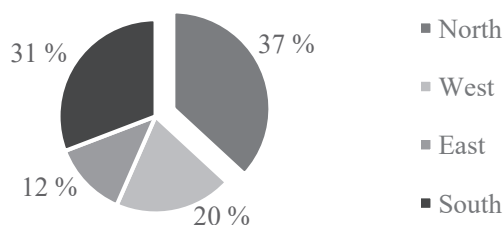


Figure 2. H12 (Region): Regional distribution of the farms across Germany (N = 207). North = Schleswig-Holstein, Lower Saxony or Mecklenburg Western Pomerania; South = Baden-Württemberg or Bavaria; East = Brandenburg, Saxony, Saxony-Anhalt or Thuringia; West = North Rhine-Westphalia, Hesse, Rhineland Palatinate or Saarland (German average: North = 20 %, West = 24 %, East = 7 %, South = 47 %). H = Hypothesis.

Therefore, this sample may be biased in favour of young, male, full-time, university-educated farmers who manage large farms compared to Germany's national average. However, most participants in this sample use smartphones. Given that this study aims to identify characteristics identifying late and early adopters of smartphone users, this sample should be considered valid.

4.2. Econometric results

VIFs were estimated to determine if VIFs interfere with the model. Multicollinearity does not threaten the model since VIFs < 5. No VIFs estimated are greater than 5 (mean VIF = 1.19, max. 1.55). Furthermore, the assumption of a normal distribution of the error terms was approved as shown in section 4.3 in detail. The *F*-statistic (5.89, $p < 0.001$) is statistically significant, indicating that more than one coefficient is statistically significant different from zero. Nagelkerke Pseudo R^2 is valued at 0.306. Table 3 displays robust standard errors (SE), coefficients, and marginal effects (ME) both in years and their corresponding significance levels. Below Table 3, statistical analysis including goodness-of-fit and explanatory statements are provided. These results echo those of Pierpaoli et al. (2013) that sociodemographic variables, financial resources-related variables as well as competitive and contingent variables affect the timing of smartphone adoption of agricultural purposes.

H1: A higher farmers' age delays the timing of smartphone adoption (Age)

Given that Age as a variable is statistically significant with the expected negative sign (ME = -0.102, $p < 0.001$), this model is supportive of H1. This implies that younger farmers begin using smartphones earlier than older farmers. Accounting for the marginal effect, smartphone adoption was delayed by 0.102 years for every extra year of a farmers' age. In other words, for every 10 additional years of age, farmers would delay adopting a smartphone by 1 year on average. Literature suggests a negative correlation between age and use of agricultural technologies. Tamirat et al. (2018) proposed that young farmers are more likely to use digital innovations in agriculture; likewise, D'Antoni et al. (2012) established that

curiosity about PATs is highest among younger farmers. In specific regards to this study, it may likewise be assumed that younger farmers embrace smartphone technology earlier than their seniors. Results open the question as to whether older farmers, due to lack of digital literacy, face obstacles in adopting and using smartphones compared to younger farmers. These conclusions may provide insight to agricultural extension services to implement relevant workshops and trainings for farmers.

H2: Holding a university degree fosters the timing of smartphone adoption (Education)

H2 is not supported by this model. Education as a variable plays no statistically significant role in the timing of smartphone adoption. Additionally, the marginal effect unexpectedly lacks a positive sign (ME = -0.511, $p = 0.194$). These results imply that education does not have a significant impact on the timing of the smartphone adoption decision. This differs from Michels et al. (2020b), who concluded that the adoption of smartphones is influenced by level of education. Additionally, education was found to have no statistically significant effect on the timing of farmers' adoption of PAT (Watcharaanantapong et al. 2014). To conclude, although education is a statistically significant factor in farmers' decision about whether to adopt smartphones, it is not considered to influence the timing of this decision.

H3: Being a male farmer fosters the timing of smartphone adoption (Gender)

The marginal effect of Gender as a variable is statistically significant according to the model with the expected positive sign (ME = 1.863, $p = 0.040$). Therefore, this model supports H3. These results indicate that male farmers begin to use smartphones prior to female farmers by two years on average. Along these lines, Michels and Musshoff (2020) found that male farmers use agricultural apps more intensively than their female counterparts. In comparison, Michels et al. (2020b), did not find a statistically significant effect of gender on the adoption decision in general. Therefore, it is understood that although female farmers adopt smartphones at the same rate as males, they are more likely to hesitate when making this decision. This result is meaningful to policymakers interested in promoting technology to female farmers. However, the cohort of women participating in this survey was small. Therefore, it must be considered that these results should be treated with caution.⁶

H4: Having a laptop or PC fosters the timing of smartphone adoption (Laptop, PC)

The marginal effect of the variable PC (ME = 0.005, $p = 0.988$) and Laptop (ME = 0.323, $p = 0.397$) have the expected positive signs. However, since they are not statistically significant, H4 is not supported by this model. It is proposed by Paustian and Theuvsen (2017) that

⁶ Section 4.3, Table 4 shows a tobit regression model without the variable Gender. However, the results stay the same proving that the model is robust.

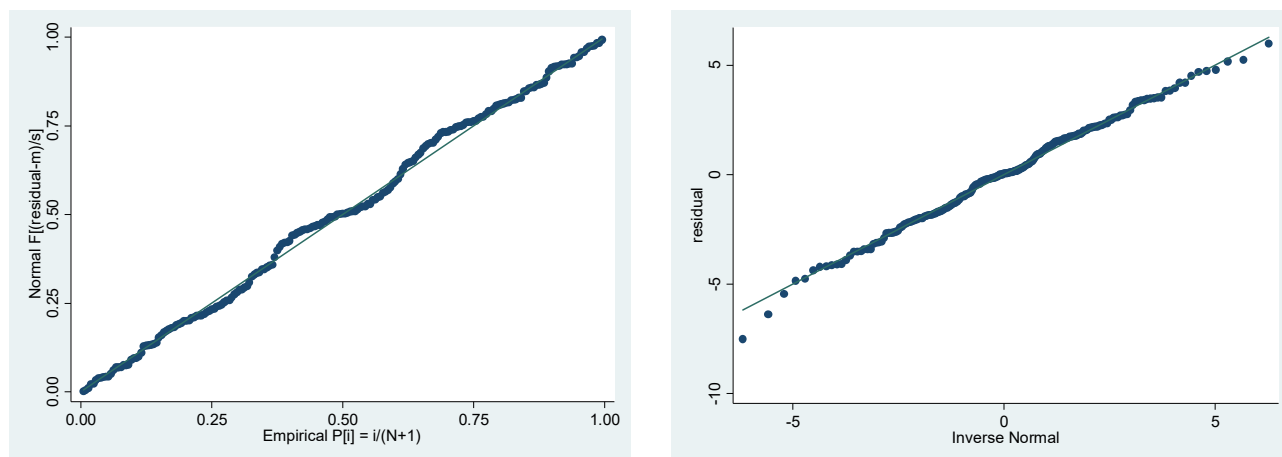


Figure 3. P–P-plot and Q-plot.

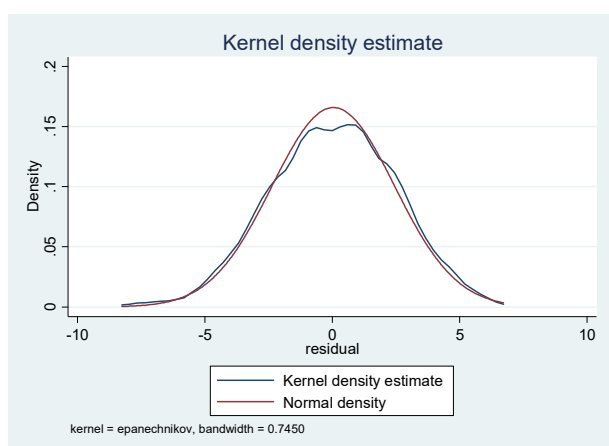


Figure 4. Kernel density plot.

computer literacy is generally high among farmers; therefore, the pervasiveness of computer skills leads to no statistically significant effect being determined through this survey. Nevertheless, the modern use of smartphones to collect data via drones (Puri et al. 2017; Sylvester 2018) could lead farmers' digital skills, for example in data formatting, to have a more important effect.

H5: A less risk-averse attitude has a positive effect on the timing of adoption (*RiskAtt*)

The model results are supportive of **H5**. Results suggest that less risk-averse farmers are more likely to be early adopters of smartphones, as demonstrated by the expected positive sign ($ME = 0.226$, $p = 0.028$) and statistically significant effect of the variable *RiskAtt*. Based on the scale used in this survey, a one-point decrease causes a 0.226-year delay in smartphone adoption. Inherent risks accompany the use of newly developed technologies; in the case of smartphones, farmers may face compatibility issues with their expected field of application or concerns regarding data protection. These risks may sway risk-averse farmers to delay the smartphone adoption decision. While the increasing prevalence of smartphones may reduce the general risk attitude towards smartphone use, a higher risk may continue to be perceived in some areas, for example in the use of financial apps due to data protection issues as described by Michels and Musshoff (2020). For these reasons, developers of agricultural apps and agricultural extension services should provide education to clarify relevant risks regarding use of smartphones and related technologies in agriculture.

H6: Being an agricultural contractor fosters the timing of smartphone adoption (*Contractor*)

The variable *Contractor* has the expected positive sign with a statistically significant marginal effect ($ME = 0.786$, $p = 0.036$). Therefore, the model supports **H6**. Results show that farmers who provide contract work adopt smartphones nearly one year earlier on average than other farmers. This correlation may stem from the multifunctionality of smartphones as organizational tools. Contract farmers are in contact with multiple farm sites and may therefore benefit from the organizational power of smartphones over regular mobile phones (Fecke et al. 2018). It is practical that these contacts, site locations, and customer orders may be saved in smartphones. Moreover, navigating to different farm sites over large distances may be made easier by a smartphone-enabled navigation app (Michels et al. 2019c).

H7: Being a full-time farmer has a positive effect on the timing of adoption (*FullTime*)

H7 is not supported by the model since the variable *FullTime* lacks the expected positive sign ($ME = -1.520$, $p = 0.020$), despite its statistical significance. Full-time farmers may profit more from smartphones and agricultural apps since they are fully focused on their farm operation, hence the expected positive sign. Contrary to expectations, results demonstrate that full-time farmers delay smartphone adoption 1.5 years longer than their part-time counterparts. Along these lines, Batte (2005) demonstrated a greater likelihood of PC adoption among part-time than full-time farmers. This may be explained by part-time farmers' higher contact with non-agriculture related communities⁷ that have higher smartphone usage and greater digital literacy. Education about PAT and digital technologies are often absent from agricultural training programs (Reichardt and Jürgens 2009). Although results do not show education having a statistically significant influence on the timing of adoption (**H3**), this study implies that full-time farmers would benefit greatly from increased education on digitalization in agricultural training programs due to having less exposure in their day-to-day lives.

H8: Being the farm manager fosters the timing of smartphone adoption (*Position*)

Survey participants' role on the farm (*Position*) was analysed regarding the timing of their smartphone adoption, with the role as farm

⁷ The reader should bear in mind that besides the proclaimed benefits and technological developments, digitalization in agriculture still lags behind other sectors (Xin et al. 2015).

Table 3. Tobit results for the timing of smartphone adoption (N = 207).^a

H	Variable	Coefficient	Robust SE	ME	p-Level	Support H?
Socio-demographic variables						
H1	Age	-0.107	0.021	-0.102***	<0.001	Yes
H2	Education	-0.532	0.410	-0.511	0.194	No
H3	Gender	1.941	0.944	1.863**	0.040	Yes
H4	Laptop	0.336	0.396	0.323	0.397	No
	PC	0.006	0.405	0.005	0.988	
H5	RiskAtt ^b	0.236	0.107	0.226**	0.028	Yes
Financial resources related variables						
H6	Contractor	0.819	0.389	0.786**	0.036	Yes
H7	Full-time	-1.584	0.686	-1.520**	0.020	No
H8	Position ^c					No
	FarmSuccessor	0.427	0.510	0.412	0.404	
	Other	-0.770	0.672	-0.730	0.246	
Competitive and contingent variables						
H9	Apprentice	0.847	0.466	0.813*	0.069	Yes
H10	Conv	0.794	0.539	0.762	0.142	No
H11	FarmSize	<0.001	<0.001	<0.001*	0.070	Yes
H12	Region ^d					Yes
	North	0.890	0.430	0.857**	0.038	
	West	-0.069	0.486	-0.065	0.887	
	East	0.356	0.731	0.340	0.627	

^a Dependent variable *SmExp**; $F(17, 190) = 5.67$, $p < 0.001$; Log pseudolikelihood = -474.27; Nagelkerke Pseudo $R^2 = 0.306$, Cox-Snell Pseudo $R^2 = 0.304$, McFadden Pseudo $R^2 = 0.073$; 0 right-censored observations, 198 uncensored observations, 9 left-censored observations at *SmExp* ≤ 0 according to Eq. (3).

^b Risk attitude measure on the scale developed by Dohmen et al. (2011) with 0 – 4 = risk-averse, 5 = risk neutral, 6 – 10 = risk-seeking.

^c Farm manager was set as the base category.

^d South was set as the base category.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SE = Standard errors, ME = Marginal effects, H = Hypothesis.

manager set as the base category in the econometric analysis. Marginal effects are thereby interpreted in that regard. H8 is not supported by the model given that marginal effects for the variables *Other* (ME = -0.730, $p = 0.246$) and *FarmSuccessor* (ME = 0.412, $p = 0.404$) are not statistically significant. However, the cohort of farmers participating in this survey who were other family members or employees was small. Therefore, the robustness of these results must be regarded with caution.⁸

H9: A farm serving as a training location for agricultural apprentices fosters the timing of smartphone adoption (*Apprentice*)

Farmers who host agricultural apprentices were expected to adopt smartphones earlier than those who do not (H9), as supported by the tobit model. The marginal effect of the variable *Apprentice* has the expected positive sign and is statistically significant (ME = 0.813, $p = 0.069$). On average, those farmers who take on interns begin to use smartphones one year before those who do not. This may be due to increased exposure to agricultural apps and other smartphone uses. Additionally, there may be a perceived expectation that farm managers are familiar with innovations in agricultural technologies that could spur them to adopt smartphones for this purpose. Policy makers should consider these results in the design of agriculture training programs to include digitization.

H10: Managing a conventional farm fosters the timing of smartphone adoption (*Conv*)

H10 is not supported by the tobit model. Although the variable *Conv* has the expected positive sign (ME = 0.762, $p = 0.142$), the marginal effect of the variable *Conv* lacks statistical significance. Organic farmers

are considered to use agricultural apps less than conventional farmers, as shown by Michels and Musshoff (2020). However, these results imply that no statistically significant difference exists in the timing of smartphone adoption based on style of farm management, whether organic or conventional. This may be because of the use of different sales channels. For example, the direct-to-consumer (DTC) channel which is popular with organic farmers (Corsi et al. 2018; Spiller 2006). In direct sales, a smartphone may serve as an organisational tool to communicate with customers and keep records. Therefore, use of smartphones may vary between organic and conventional farmers, but timing of adoption is not statistically significant.

H11: A higher farm size in hectares arable land fosters the timing of smartphone adoption (*FarmSize*)

This model supports H11 given that the variable *FarmSize* carries the expected positive sign (ME = < 0.001, $p = 0.070$) and is statistically significant. The marginal effect on adoption timing is minor, however, at a greater scale, each additional thousand hectares of land leads to an earlier smartphone adoption time of less than one year on average. Given that PAT come at a higher cost than smartphones (Pongnumkul et al. 2015), this cannot be explained by economies of scale. PAT are more often used on larger farms, which could thereby also implement smartphones as a tool (Michels et al. 2020b). With a farm's increasing size comes greater organisational complexity which could be more easily managed using smartphones.

H12: Location of the farm in the southern region of Germany with less mobile internet coverage delays the timing of smartphone adoption (*Region*)

Results of H12 for the variable *Region* must be referred to from the base category, which in this case is the southern region due to its

⁸ Section 4.3, Table 4 shows a tobit regression model without the variable Position. However, the results stay the same proving that the model is robust.

Table 4. Tobit regression results without the variables *Gender (H3)* and *Position (H8)* (N = 207).^a

H	Variable	Coefficient	Robust SE	ME	p-Level	Support H?
Socio-demographic variables						
H1	Age	-0.110	0.019	-0.106***	<0.001	Yes
H2	Education	-0.592	0.396	-0.568	0.134	No
H4	Laptop	0.195	0.393	0.187	0.619	No
	PC	-0.026	0.415	0.005	0.946	
H5	RiskAtt ^b	0.245	0.112	0.235**	0.028	Yes
Financial resources related variables						
H6	Contractor	0.823	0.401	0.794**	0.042	Yes
H7	Full-time	-1.637	0.689	-1.569**	0.017	No
Competitive and contingent variables						
H9	Apprentice	0.766	0.455	0.734*	0.092	Yes
H10	Conv	0.856	0.563	0.820	0.129	No
H11	FarmSize	<0.001	<0.001	<0.001*	0.079	Yes
H12	Region ^c					Yes
	North	0.911	0.442	0.877**	0.039	
	West	-0.106	0.493	-0.101	0.828	
	East	0.159	0.772	0.152	0.836	

^a Dependent variable *SmExp*; $F(13, 194) = 6.27, p < 0.001$; Log pseudolikelihood = -478.891; Nagelkerke Pseudo $R^2 = 0.274$, Cox-Snell Pseudo $R^2 = 0.272$, McFadden Pseudo $R^2 = 0.0643$; 0 right-censored observations, 198 uncensored observations, 9 left-censored observations at $SmExp \leq 0$ according to Eq. (3).

^b Risk attitude measure on the scale developed by Dohmen et al. (2011) with 0 – 4 = risk-averse, 5 = risk neutral, 6 – 10 = risk-seeking.

^c South was set as the base category.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, SE = Standard errors, ME = Marginal effects, H = Hypothesis.

relatively weak mobile internet network among the four regions of Germany evaluated in the survey. Results indicate that farmers in the southern regions delay smartphone adoption by 0.857 years on average compared to those in the north. The marginal effect was found to be statistically significant with the expected positive sign (ME = 0.857, $p = 0.038$). Between eastern, western and southern German farmers, there was no difference of statistical significance found (West, ME = -0.065, $p = 0.887$; East, ME = 0.340, $p = 0.627$). This corroborates the results of Michels et al. (2020c), which shows that farms in the north of Germany have higher use of mobile phones because of more widespread internet coverage. It goes to reason that a weak mobile internet network could dissuade farmers from smartphone adoption, since smartphones cannot be used to their full potential without a wireless connection. Therefore, it is in the interest of policymakers to emphasize the expansion of mobile internet networks to foster earlier smartphone adoption.

4.3. Robustness, limitations and outlook

Table 4 shows the regression results without the variables *Gender (H3)* and *Position (H8)*. However, the results stay the same proving that the model is robust.

Figure 3 show the P–P plot and the Q-plot. Both graphs shown only minor deviation from normality. Likewise, the kernel density plot in Figure 4 shows only small deviation from normality. Hence, from looking at Figures 3 and 4, residuals are close to normal distribution.

Table 5 shows the results for the inter-quartile range. Having severe outliers provides evidence to reject normality which is not case. Furthermore, the trimmed mean is close to the mean and median which indicates a symmetrical distribution. Lastly, a non-statistically significant Shapiro-Wilk W test for normality ($W = 0.995, p = 0.768$) provides further evidence for the normality of the residuals.

By using a non-probability sampling method, the generalization of the results should be treated with caution. This study would benefit from

Table 5. Results for the inter quartile range.

Mean = 0.0427	Std. dev. = 2.405	N = 207
Median = 0.0585	Pseudo std. dev = 2.584	IQR = 3485
Trimmed mean = 0.0696		
	Low	High
Inner fences	-6.940	7.001
Number of mild outliers	1	0
% mild outliers	0.48 %	0.00 %
Outer fences	-12.17	12.23
Number of severe outliers	0	0
% severe outliers	0.00 %	0.00 %

better representation in the sampling technique of future repetitions in order to enable broader generalization. Future investigations could explore the timing of smartphone adoption in regards to certain popular agricultural apps or digital services. Finally, it would be interesting to verify if farmers' early adoption of smartphones improves farm management practices and, if so, to which degree.

Although the scope of this investigation was limited to Germany and therefore restricted in its generalization, the framework and results could be applied to developing countries in future research. Smartphones play a key role in emerging and developing countries by enabling internet access at a low cost. Given that smartphone adoption is relatively delayed in developing countries, this could make for even more relevant research going forward. Though obstacles to adoption may vary, certain trends can be expected. Since farmers' needs and technological infrastructure differ among nations, future studies should verify these outcomes in various country settings.

5. Concluding remarks

The multifunctionality of smartphones in providing access to valuable, up-to-date agricultural information and amenities provides valuable guidance to farmers and makes them a key ICT in the sustainable development and improved management of agricultural practices worldwide. The primary objective of this study was to investigate variables affecting the timing of smartphone adoption in agriculture. This was performed in 2019 by sampling 207 German farmers and using a left-censored tobit regression model estimated to determine specific features of the farmers and farm sites that influence when smartphones were adopted. This information is key to identify the groups of farmers who adopt smartphones at different timepoints. Finally, this information could be applied in order to facilitate smartphone diffusion among late-adopting farmers.

This study indicates that late adopters of smartphones are comparatively characterized as being older, female, and more risk-averse farmers from smaller farms. Additionally, hosting agriculture apprentices and working as an agricultural contractor in addition to arable farming is positively correlated with early adoption of smartphones. Moreover, working as a part-time farmer and living in a region with strong mobile internet coverage have a statistically significant positive effect on timing of smartphone adoption in Germany.

These results are meaningful in their practical applications by agricultural extension services, policymakers, designers of agricultural apps and smartphone providers. Given that a farm's location impacts timing of smartphone adoption, the expansion of mobile networks should be prioritized by policymakers to promote the diffusion of smartphones in agriculture. Farm apprenticeships should aim to cover digitalization in agriculture for beginning farmers. For agricultural extension services, extra support regarding smartphone use in agriculture should be given to risk-averse, female, and older farmers as they may encounter more obstacles than other farmers to smartphone adoption. Similarly, the clarification of inherent risks to the use of smartphones and agriculture-related apps, such as data protection, should be clarified to farmers by

smartphone providers and agricultural extension services to facilitate their adoption. This paper provides multiple points for future studies to build upon.

Declarations

Author contribution statement

Marius Michels; Oliver Musshoff: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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