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Smartphone adoption and use in agriculture: empirical evidence from Germany

Marius Michels[1] · Wilm Fecke[1] · Jan-Henning Feil[1] · Oliver Musshoff[1] · Johanna Pigisch[2] · Saskia Krone[2]

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Abstract
Smartphone technology is promising for the future development of agriculture, as it can facilitate and improve many operational procedures and can also be combined with precision agriculture technologies. Yet, existing research on smartphone adoption in agriculture is scarce. Therefore, this paper empirically explores the factors influencing smartphone adoption by German farmers. The relationship between farmers, farm characteristics and smartphone adoption was analysed using a binomial logit model. The dataset, collected in 2016, consists of 817 German farmers and is representative in terms of age, farm size and diversification as well as regional distribution across the study area. The results indicate that, among other factors, farmers' age, education, and farm size are determinants of smartphone adoption. Furthermore, the paper provides descriptive information about the usage of smartphone functions and agriculture-related app functions. Thus, this paper contributes to the literature by identifying key determinants of smartphone adoption in agriculture. The findings may be of interest for policy makers, researchers in the field of precision agriculture technologies as well as developers and providers of farm equipment and precision agriculture technologies that integrate with smartphones, since the paper includes information concerning smartphone use and key factors influencing smartphone adoption.

Keywords Technology adoption · Smartphone adoption · German farmers · Digitalisation · Innovation

Introduction

Technical innovations such as computers, internet, mobile phones and smartphones, were first adopted in central urban areas and reached remote rural areas at a later stage. However, a well-functioning digital infrastructure is often needed the most in rural areas in order to overcome their remoteness and to remain attractive places for citizens to live (Salemink

✉ Marius Michels
marius.michels@agr.uni-goettingen.de

[1] Department of Agricultural Economics and Rural Development, Georg-August-Universität Göttingen, Platz der Göttinger Sieben 5, 37073 Göttingen, Germany

[2] Kleffmann Group, Mühlenstraße 1, 59348 Lüdinghausen, Germany

et al. 2017; Whitacre 2008). In many countries, rural areas are still economically and culturally characterised by agriculture to a large extent (Jeffcoat et al. 2012; Morris et al. 2017). To support agricultural development in general and effective farm management specifically, innovation adoption is seen as a crucial factor (McFadden and Gorman 2016). In this context, digitalisation as well as information and communication technologies (ICT) innovations may lead to direct production gains or cost reductions in agriculture and can improve farmers' access to and use of data and information for farm management purposes (Aker 2011; Rolfe et al. 2003).

ICT, such as mobile phones, have been utilized by farmers for a long time for these purposes. Especially in developing countries, mobile phones are the prevailing tool to gather agricultural information (Aker and Mbiti 2010; Jensen 2010), since mobile phones can reduce transaction and search costs to a great extent (Aker 2011). More specifically, mobile phones can assist farmers by providing a better connection to suppliers and customers (Mittal and Mehar 2012) as well as financial (Baumüller 2012) and extension services (Aker 2011), for instance guided fertilizer rate application (Tey et al. 2015). Recently, farmers in developing countries have also been using mobile phones for video-based learning (Maredia et al. 2018). The possibilities for farmers to utilize mobile phones for their farm business have evolved over time in congruence with the development of the computing capabilities and functions of mobile phones. In particular, a fundamental innovation in digital ICT has been the development of smartphone technology. According to Jin et al. (2013) and Kim (2014), smartphones are intelligent, portable devices with computer-like functions, traditional voice-call functions and internet access. Furthermore, smartphones offer the possibility to install or delete multiple applications (apps) according to user needs (Teacher et al. 2013).

Precision agriculture technologies (PAT) are expected to enable farmers to improve the efficiency of their farm management by reducing input use, and thereby also reducing negative environmental externalities (Borghi et al. 2016; Tamirat et al. 2018). More specifically, usage of PAT involves data collection, processing and analysis and finally, field operations based on the analysed data (Jawad et al. 2017; Tey and Brindal 2012). These steps can be assisted and facilitated by using smartphones for data transfer, management and processing operations. Furthermore, smartphones also enable an easy interaction between users and wireless sensors (WS) and allow farmers to be permanently connected with the WS systems. Farmers are thereby enabled to monitor their field or manage their WS from anywhere at any time (Barcelo-Ordinas et al. 2013; Mesas-Carrascosa et al. 2015; Abdullahi et al. 2015; Peres et al. 2011). For instance, timing of irrigation can be assisted and improved by smartphones in connection with soil moisture sensors (Vellidis et al. 2016). In addition, farmers can monitor their livestock with respect to their resting, feeding and moving behaviour in connection with sensors in precision livestock farming (Kamilaris and Pitsillides 2016). The steady connection to WS allows for improved and faster decision making. In addition, smartphones and their built-in sensors are also able to replicate or substitute several PAT to a certain extent at a lower cost and to perform agriculture-relevant calculations on their own. For instance, smartphones and related apps can be used for disease detection and diagnosis in plants, fertilizer calculation, access to market and price data, geo-referenced scouting and documentation. Moreover, smartphones and smartphone apps enable farmers to collect, store and analyse data to improve decision making (Fulton and Port 2018; Pongnumkul et al. 2015; Gligorević et al. 2015).

While the adoption of mobile phones in agriculture, especially in developing countries (e.g. Duncombe 2016; Islam and Grönlund 2011), and the adoption of precision agricultural technologies (PAT) (for a literature review see Pierpaoli et al. 2013 as well as Tey and Brindal 2012) are well understood, no prior study has analysed factors influencing explicitly smartphone adoption in agriculture. Most studies with respect to smartphone use in agriculture focus on the potential of smartphones and apps for agricultural and environmental purposes (e.g. Dehnen-Schmutz et al. 2016; Hallau et al. 2018; Pongnumkul et al. 2015; Teacher et al. 2013; Bonke et al. 2018). Despite the fact that smartphones share characteristics of mobile phones and PAT, they differ from or go beyond the mentioned technologies in some critical ways. Firstly, smartphone technology goes beyond mobile phone technology since these smart devices combine functions previously performed separately by mobile phones (voice-call functions, SMS, camera functions), PDAs (storage and organisation of information, contacts, calendar) and computers (Internet, e-mail) (Butler 2011; Jin et al. 2013; Kim 2014). Secondly, smartphones offer a higher multi-functionality than mobile phones. Smartphones are able to gather, process, and share data as well as offer a multitude of installable mobile applications (apps) according to user needs. In addition, smartphones provide users with global positioning systems (GPS) and access to geographical information systems (GIS) (Teacher et al. 2013). As a consequence, smartphones are able to integrate with PAT and facilitate use of PAT, and they may also serve as a device to realize PAT purposes by themselves at a lower cost. More specifically, apps which make use of smartphone built-in sensors to replicate or substitute PAT functions can be installed and deleted at almost no cost in contrast to the investment and disinvestment decisions for PAT. Paxton et al. (2011) stated that PAT are somewhat different from any other technology introduced to agriculture. Furthermore as shown before, smartphones differ in some crucial ways from mobile phones and PAT. Thus, factors influencing the adoption of smartphones might differ from adoption patters of PAT and mobile phones as well, as noted also by Kernecker et al. (2016, p. 21), who stated that "mobile phone ownership do not correspond to any other patterns related to smart farming technology adoption […]". Consequently, it is worthwhile to identify determinants of smartphone adoption in agriculture.

Understanding determinants of adoption is important in order to improve user acceptance and use of technology, especially in the case of farmers as they can take part in the development process (Cavallo et al. 2014; Glenna et al. 2011). To develop and offer more needs-tailored apps with respect to smartphones and to increase farmers' awareness of the associated advantages, it is crucial to understand the drivers and obstacles for smartphone adoption. Moreover, understanding factors affecting smartphone adoption in agriculture could also facilitate the widespread use of data-driven PAT which integrate with smartphones. Furthermore, no study has yet documented smartphone use in terms of apps and functions in agriculture. For the further development of needs-tailored apps for farmers, it is also important to assess the current usage behaviour with respect to used functions and apps.

Against this background and to fill this research gap, the objective of this paper is to analyse key determinants of German farmers' smartphone adoption and shed light on the usage of several smartphone functions and agriculture-related apps. The dataset consists of 817 observations and was sampled to be representative in terms of farmers' age, farm diversification, farm size and regional distribution in Germany. A binomial logit model is applied to identify key factors influencing farmers' smartphone adoption. With this approach, this study builds on previous studies in the field of agriculture with regard to adoption decisions for information technologies such as computers, the internet and precision agriculture (Batte 2005; Carrer et al. 2017; Gloy and Akridge 2000; Tey and Brindal 2012). Thus, this paper contributes to the literature by identifying key determinants of smartphone adoption in agriculture. In particular, this study also adds to the literature by evaluating whether smartphone adoption patterns differ from PAT adoption patterns as the literature suggests. Moreover, this study assesses the current use of smartphone functions by farmers and the utilization of agriculture-related smartphone apps. The findings of this study provide valuable information concerning smartphone use and key factors influencing smartphone adoption, and therefore may be of interest for policy makers, researchers in the field of PAT as well as developers and providers of farm equipment and PAT that integrate with smartphones.

The rest of the paper is organised as follows: In "Factors influencing farmers' smartphone adoption" section, several research hypotheses are derived on the basis of a literature review. In the subsequent "Data collection and descriptive statistics" section, descriptive statistics and the applied econometric model are presented. Results of the binomial logit model estimation are displayed and discussed in "Results and discussion of the econometric analysis" section. Lastly, the paper ends with the final remarks on the practical implications of the study and areas for future research.

Factors influencing farmers' smartphone adoption

The widespread theory on diffusion of innovation by Rogers (2003) has been applied in several scientific disciplines to explain technology adoption by individuals, social groups or organizations.[1] The theory considers several variables which are expected to influence adoption. This set of variables includes adopter characteristics as well as firm characteristics. In accordance with this, hypotheses that might influence smartphone adoption are derived from an extensive literature review. Consequently, the hypotheses consider farmers' characteristics (*H1–H5)* and farm characteristics (*H6–H8*). Since smartphones share several characteristics with PAT, this section refers to literature dealing with PAT adoption. Furthermore, modern smartphones are akin to laptops with internet access (Wang et al. 2014). Therefore, literature with respect to computer and internet adoption in agriculture is also considered. Lastly, scientific results concerning smartphone adoption in the general public are taken into account.

Farmer characteristics

One of the key characteristics often discussed in the agricultural economics literature is farmers' age, which is expected to influence technology and innovation adoption to a great extent (Ghadim and Pannell 1999). According to Tamirat et al. (2018) younger farmers were more likely to adopt PAT due to higher interest in new technologies. Furthermore, Tiffin and Balcombe (2011) showed that increasing age of British farmers decreased the likelihood of using a computer. Likewise, in the case of smartphone adoption decisions, the age of the decision maker also plays a significant role. A recent study by Kongaut and Bohlin (2016) found that smartphone adoption in Sweden was less likely for older people than for younger people. Taking the aforementioned studies into account, the following hypothesis can be derived:

[1] For an overview see Dedehayir et al. (2017).

H1 Older farmers are less likely to own a smartphone.

It is expected that farmers' education affects the technology adoption decision (Lin 1991). However, with respect to the adoption of PAT, the literature is mixed. Daberkow and McBride (2003) showed that a higher education level was positively linked to PAT awareness, but not to actual adoption. However, Walton et al. (2008) found that higher education increases the likelihood that a farmer adopts PAT. Likewise, education level was thought to be an important influencing factor for computer and internet adoption in agriculture (Briggeman and Whitacre, 2010; Carrer et al. 2017; Smith et al. 2004). With respect to smartphones, Kongaut and Bohlin (2016) found that lower levels of education resulted in a lower probability of having a smartphone. Therefore, the following hypothesis will be tested:

H2 More highly-educated farmers are more likely to own a smartphone.

Gender plays a distinctive role in decision processes that drive information technology adoption (Venkatesh et al. 2000). With respect to PAT adoption, Paustian and Theuvsen (2017) noticed that gender has not been recognized as an important determinant in PAT adoption since most farmers are assumed to be male. However in agriculture in general, male farmers tended to be more likely to adopt a new technology or innovation than female farmers (Doss and Morris 2000). Furthermore, Adamides et al. (2013) found that male Cypriot famers had a statistically significantly higher probability of using a PC than female farmers, but no effect of gender was found for internet usage. No statistically significant effect of gender on smartphone adoption was found by Puspitasari and Ishii (2016) for Indonesian citizens. Although the literature is not in total agreement, the following hypothesis is proposed:

H3 Male farmers are more likely to own a smartphone.

Prior experience with an information technology is expected to positively influence the adoption of a similar technology (Taylor and Todd 1995). In line with this, Ghadim and Pannell (1999) suggested the same for the agricultural context. They illustrated that a farmer who has already managed to learn some technical skills required by a certain technology may therefore more easily learn to use a similar or more advanced technology. Computer literacy also plays an important role in PAT adoption since computer technology is an integral part of PAT. Computer use implies that a farmer has some knowledge and skills with respect to technological operations (Tey and Brindal 2012). Moreover, recent smartphones already have the same computational capabilities as laptops with internet access (Wang et al. 2014). Therefore, the following hypothesis will be tested:

H4 Computer literacy increases the probability that farmers own a smartphone.

Attitudes and beliefs of a decision maker should also be considered in the adoption analysis (Karahanna et al. 1999). A person's innovativeness, defined as the willingness to test new technologies (Godoe and Johansen 2012), has been identified as a crucial personal trait influencing the adoption of new technologies (Hirschman 1980). In terms of agriculture, Aubert et al. (2012) found that innovativeness had a significant and positive effect on PA technology adoption. With respect to smartphones, Lee (2014) showed that a high self-reported innovativeness of US college students positively affected the smartphone adoption decision. Hence, the following hypothesis is proposed:

H5 Self-reported innovativeness of farmers increases the probability that farmers own a smartphone.

Farm characteristics

The literature has shown that larger farms are more likely to be adopters of PAT, mainly due to economies of scale (Pierpaoli et al. 2013; Tey and Brindal 2012). Farm size also plays a central role in computer and internet adoption decisions. Gloy and Akridge (2000) found a positive relationship between farm size and computer adoption, but described the effect as rather small. Moreover, Mishra and Park (2005) suggested that farm size increased the number of internet applications used for business purposes by US farmers. Regarding literature on smartphone adoption in general, Ortbach et al. (2014) showed that firm size had a significant and positive effect on smartphone adoption in organisations. The following hypothesis is therefore to be taken into account:

H6 Farmers from smaller farms are less likely to own a smartphone.

Enterprise diversification has been shown to have no statistically significant effect on the adoption of PAT (Walton et al. 2008). According to Amponsah (1995), there was also no effect of diversification on computer adoption in agriculture. In contrast to that, Mishra and Park (2005) argued that more diversified farms require that farmers make more decisions and gather more information and therefore were more likely adopt the use of a computer and the internet. Along the same lines, it is conceivable that farmers running a more diversified farm are more likely to adopt a smartphone due to the multi-functionality of this device. Therefore it can be hypothesized:

H7 Farmers from more diversified farms are more likely to own a smartphone.

For PAT adoption, location of the farm also plays an important role due to differences in climatic, soil and topographic conditions (Paxton et al. 2011). With respect to ICT, the digital infrastructure of the location is assumed to play a role as either an enabler for or barrier to adoption. For instance, territorial based barriers to accessing the internet are often the result of the geography of digital infrastructure (Philip et al. 2017). Regarding mobile internet, place of residence also plays a prominent role due to digital infrastructure (Srinuan et al. 2012). Smartphone apps and also integration with PAT can rely on mobile internet coverage which depends on the digital infrastructure. Data from the TÜV Rheinland (2017, see Table 4 in the "Appendix") suggest that mobile internet coverage is relatively less developed in the southern region of Germany (Baden-Württemberg and Bavaria) compared to the other regions. Therefore, the following hypothesis will be tested:

H8 Location of the farm in the southern region of Germany has a statistically significant negative effect on smartphone adoption.

Materials and methods

Data collection and descriptive statistics

The survey was carried out in Germany in 2016. In 2016, there were about 275.000 farms in Germany cultivating 11.8 million hectares of arable land. Data collection through computer-assisted telephone interviews (CATI) and web interviews (CAWI) with personalised links was performed by the *Kleffmann Group*. Using personalised links ensured that farmers can only participate once in the survey. Moreover, the survey was addressed solely to German farmers and, more specifically, to the farm operator; this was safeguarded with a screening question before the actual survey. The final sample (response rate 10%) was selected randomly from a quota sample of farmers constructed by the *Kleffmann Group*. The quota sample was constructed to be representative in terms of distribution of age, regional distribution, farm size and diversification according to information from the German Federal Statistical Office (Destatis). It should further be noted that only farmers who cultivate at least 20 hectares of arable land were interviewed. Given this exclusion of small farm size classes, the representativeness of the dataset was therefore ensured with respect to the distribution of the remaining farm size classes in German agriculture (Destatis 2014; German Farmers'Federation 2014).

Table 1 shows the descriptive statistics for all variables that were used for the econometric analysis. Smartphone ownership is the dependent variable in the econometric analysis. 58.50% of the interviewed farmers owned a smartphone. In 2016, 74% of the general German population owned a smartphone (Statista, 2017), which lies above the average for the German farmers in this study. Of those farmers who own a smartphone, 50.20% used professional apps for agricultural purposes. The average respondent was 49 years old. Table 1 also shows the distribution across several age classes. For instance, 13.50% of the surveyed farmers were younger than 35 years (*H1*). With respect to education, 17.40% of the participating farmers held a university degree (*H2*) and 89.60% of the participating farmers were male (*H3*). In Germany, on average 12% of farmers held a university degree and 90% were male in the same year. Thus, the sample is also representative with respect to gender. However, it should be noted that it was not sampled to be representative of farmers' gender. Around 58.80% of the participating farmers had a laptop and 90.80% had a computer (*H4*). Furthermore, the participating farmers were asked to indicate their level of innovativeness on a 5-point Likert scale. The variable measured through the equally-spaced Likert scale is treated as a continuous variable. On average, the participating farmers tended to perceive themselves as not very innovative (2.263) when it comes to technological innovations (*H5*). Moreover, participating farmers cultivated 125 hectares of arable land on average. Table 1 also provides information on the distribution among the farm size classes. For instance, 30.50% of the farmers in the sample cultivated 20–50 hectares of arable land (*H6*). To consider the effect of the diversification of the farms on farmers' smartphone adoption decisions, the model included the degree of diversification measured by the Berry index. The Berry index was obtained by the following calculation:

$$BI_i = 1 - \Sigma p_j^2 \tag{1}$$

where BI_i denotes the Berry index for the farm i and p_j denotes the share of each farm activity j in the total turnover. Values for the Berry index range from 0 to 1. The higher the Berry index, the more diversified the farm is (Berry 1971). The average Berry index

Table 1 Descriptive statistics (n = 817)

	Variable	Definition	Mean	S.D.	Min	Max	German average[e]
	Smartphone	1 if the farmer had a smartphone; 0 otherwise	0.585	–	0	1	n. a.
	Professional apps[a]	1 if the farmer used apps for agricultural purposes; 0 otherwise	0.502	–	0	1	n. a.
H1	Age[b]	Farmers' age in years	48.745	11.173	16	85	53
	Age group 1	< 35 years	0.135	–	0	1	0.203
	Age group 2	35–45 years	0.231	–	0	1	0.191
	Age group 3	46–55 years	0.347	–	0	1	0.296
	Age group 4	> 55 years	0.287	–	0	1	0.300
H2	Education	1 if the farmer held a university degree; 0 otherwise	0.174	–	0	1	0.120
H3	Gender	1 if the farmer is male; 0 otherwise	0.896	–	0	1	0.900
H4	Computer literacy	1 if the farmer had a laptop; 0 otherwise	0.588	–	0	1	n. a.
		1 if the farmer had a computer; 0 otherwise	0.908	–	0	1	n. a.
H5	Self-reported innovativeness[c]	"As soon as a technological innovation is launched on the market, I am very interested in testing it."[d]	2.263	1.070	1	5	n. a.
H6	Farm size[b]	Farm size in hectares of arable land	124.661	257.093	20	3700	60.50
	Farm size class 1	20–50 hectares of arable land	0.305	–	0	1	0.458
	Farm size class 2	50.01–100 hectares of arable land	0.395	–	0	1	0.323
	Farm size class 3	100.01–200 hectares of arable land	0.214	–	0	1	0.178
	Farm size class 4	> 200.01 hectares of arable land	0.090	–	0	1	0.040
H7	Diversification	Diversification measured by the Berry index	0.255	0.225	0	0.770	n. a.
H8	North	Farm is located in Schleswig–Holstein, Lower Saxony or Mecklenburg Western Pomerania	0.249	–	0	1	0.210
	East	Farm is located in Brandenburg, Saxony, Saxony-Anhalt or Thuringia	0.069	–	0	1	0.071

Table 1 (continued)

Variable	Definition	Mean	S.D.	Min	Max	German average[e]
South	Farm is located in Baden-Württemberg or Bavaria	0.423	–	0	1	0.474
West	Farm is located in North Rhine-Westphalia, Hesse, Rhineland Palatinate or Saarland	0.257	–	0	1	0.249

[a]Mean shown as a ratio for smartphone = 1

[b]Age group and farm size classes were used in the econometric analysis

[c]Likert scale in which 1 = does not describe me at all; 5 = describes me well

[d]Translated from German into English

[e]Destatis (2014), German Farmers' Federation (2014)

Source: Authors' calculations and illustration

Table 2 Famers' use of smartphone functions (n = 478) and professional apps (n = 240)

Function	Percent reporting use	App	Percent reporting use
Phone calls	94.56	Information and news	71.25
Messaging	67.36	Pest and weed control	60.00
Using the camera	66.31	Market data: costs and prices	57.08
Using apps	60.04	Farm management and data collection	42.50
Organizing appointments	43.72	Herd management and data collection	29.16
Surfing on internet	42.88	Animal healthcare	23.33
Writing E-mails	34.30	Fertility and breeding	21.66
Social networks	28.66	Animal feeding	12.50
Listening to music	13.80	Financial farm management	12.91
Games	7.94	Weather apps	3.75
Navigation	0.41	Others	0.04

Multiple answers possible

Source: Authors' illustration and calculation

was 0.255 (*H7*). 817 out of 829 farmers interviewed within the survey were included in the analysis since they answered the required questions for the calculation of the Berry index completely. The data also provides information concerning the regional distribution. For instance, 25.70% of the farms are located in the region west *(H8)*.

In the sample, 478 famers have a smartphone of which 240 farmers have their smartphones equipped with professional agriculture-related apps. Table 2 lists the percentage of farmers who used a smartphone function or apps. To avoid potential bias by asking for available apps, which might not be known to all farmers in the sample, farmers were asked about functions instead of apps. Furthermore, by asking about functions instead of specific apps the results are also of interest to agricultural sectors and developers of apps beyond Germany. 94.56% of these farmers stated using their smartphones for phone calls. In addition, messaging is used by 67.36% of the farmers. Thus, smartphones are most used for communication. Concerning other smartphone functions, using the camera (66.31%), or apps in general (60.04%) are the most stated functions used on smartphones. From the 478 farmers who have a smartphone, 50.02% used apps for agricultural purposes. 71.25% of these farmers used information and news apps. Furthermore, more than half of the farmers used apps for pest and weed control (60.00%) and the assessment of market information (57.08%). Besides obtaining information, data collection apps for farm and herd management are also frequently used by farmers (42.50% and 29.16% respectively). Hoffmann et al. (2014) investigated the smartphone apps available for use by farmers. They showed that most smartphone apps accessible to farmers offer functions with respect to information, documentation and analysis, which mirrors farmers' reported use of apps with these specific functions (information and news 71.25%, market data, costs and prices 57.08%, farm management and data collection 42.50%). Furthermore, Hoffmann et al. (2014) showed that most smartphone apps available provide functions with respect to plant production. Only a few available apps assist farmers in animal production (Hoffmann et al. 2014). This is congruent to the reported use by the farmers in the study at hand (pest and weed control 60.00%, herd management and data collection 29.16%, animal healthcare 23.33%).

Econometric model

Adoption decisions can be modelled as binary choices (1 = yes; 0 = no) using probit or logit models. The decision can then be related, for instance, to adopters' characteristics (Aldrich and Nelson 1984). With respect to smartphone adoption, there have also been studies using probit and logit models (Kongaut and Bohlin 2016; Lee 2014). Specifically, these models have often been used to identify determinants of farmers' computer and internet adoption in agriculture (Gloy and Akridge 2000) as well as precision agriculture technologies (Pierpaoli et al. 2013). However, there is no clear preference in the literature for probit or logit models. For most applications, it makes no difference since they provide identical conclusions (Gill 2000) by producing very similar marginal effects (Dill et al. 2015). Still, Tey and Brindal (2012) noticed that for most precision agricultural adoption studies a logit model was applied. Assuming a standard logistic distribution of the error term ε_i (Verbeek 2008), a binomial logit model to analyse German farmers' smartphone adoption with the following specifications is applied:

$$y_i^* = \beta' x + \varepsilon_i \tag{2}$$

Thus, y_i^* is a dichotomous (0, 1) latent variable indicating whether farmer i owns a smartphone. For the explanatory variables, x is a vector containing farmer and farm characteristics. If farmer i owns a smartphone, the estimators of β reflect the effects of changes in the explanatory variables on the probability of a farmer adopting a smartphone. ε_i denotes an error term. In order to test whether the model fits the data, necessary specification tests were performed which are displayed in the following section.

Results and discussion of the econometric analysis

A binomial logit model with a total of 817 observations was estimated to determine farmer and farm characteristics that influence farmers' smartphone adoption decisions. Estimated coefficients, marginal effects and related standard errors are depicted in Table 3. Marginal effects show the variation in the dependent variable as a response to a discrete change in an independent variable, *ceteris paribus*. The p-values (P) for the marginal effects are reported in the fifth column. The model was statistically significant, as shown by a likelihood-ratio (LR) test ($P < 0.001$). Hence, the null hypothesis that all coefficients are statistically equal to zero was rejected. The McFadden pseudo R-squared was 0.222, indicating a relatively good fit (McFadden 1977). Furthermore, the Pearson as well as the Hosmer–Lemeshow test were not statistically significant, indicating no misspecification of the model ($P > 0.1$) (Cameron and Trivedi 2010). Standard errors might be biased if two or more explanatory variables are highly correlated (Mansfield and Helms 1982). To test for multicollinearity, variance inflation factors (VIFs) were calculated ranging from 1.02 to 1.09 with a mean of 1.05. A VIF smaller than 10 suggests that multicollinearity is not present (Curto and Pinto 2011). The model predicted 74.66% of the observations correctly, which is comparable to results of computer and internet adoption studies with farmers (Batte 2005; Briggeman and Whitacre 2010; Gloy and Akridge 2000).

Table 3 Estimation results of the binomial logit model (n = 817)

	Variable	Coefficient	Marginal effect	P-level	Std. error
H1	Age group 2 (35–45 years)[a]	– 1.148	– 0.161	< 0.001***	0.046
	Age group 3 (46–55 years)[a]	– 1.939	– 0.315	< 0.001***	0.044
	Age group 4 (> 55 years)[a]	– 2.661	– 0.464	< 0.001***	0.047
H2	Education	0.404	0.071	0.087*	0.041
H3	Gender	0.106	0.018	0.705	0.049
H4	Computer literacy (laptop)	1.118	0.209	< 0.001***	0.026
	Computer literacy (computer)	0.816	0.144	0.006***	0.052
H5	Innovativeness	0.300	0.053	< 0.001***	0.013
H6	Farm size class 1 (20–50 hectares)[b]	– 1.089	– 0.182	0.003***	0.061
	Farm size class 2 (50.01–100 hectares)[b]	– 1.056	– 0.176	0.003***	0.059
	Farm size class 3 (100.01–200 hectares)[b]	– 0.984	– 0.163	0.007***	0.060
H7	Diversification	– 0.033	– 0.005	0.928	0.065
H8	North[c]	0.608	0.109	0.006***	0.040
	East[c]	0.287	0.052	0.467	0.071
	West[c]	0.941	0.166	< 0.001***	0.036

[a]Age group 1 (< 35 years) was set as the base category in the econometric analysis

[b]Farm size group 4 (> 200 hectares of arable land) was set as the base category in the econometric analysis

[c]South was set as the base category in the econometric analysis

Level of significance *P < 0.1, **P < 0.05 and ***P < 0.01; LR chi2 (15) = 246.58, P < 0.001; Pearson chi2 (723) = 740.06, P = 0.3218; Hosmer–Lemeshow chi2 (8) = 13.27, P = 0.1030; Mc-Fadden Pseudo $R^2 = 0.222$ Cox-Snell Pseudo $R^2 = 0.261$; Nagelkerke Pseudo $R^2 = 0.351$; Correctly classified 74.66%

Source: Authors' calculations and illustration

H1 Older farmers are less likely to own a smartphone.

The model shows evidence to support Hypothesis 1. The coefficients of the age groups 2 to 4 have the expected negative signs and the marginal effects are statistically significant. The results indicate that farmers older than 35 years are less likely to be smartphone owners than farmers who are younger than 35 years. For instance, farmers in the age group between 35 and 45 years are 16.10% less likely to be smartphone owners than farmers in the reference group. Moreover, being a farmer older than 55 years decreases the likelihood of owning a smartphone by about 46.4% in comparison to the reference group, which was younger than 35 years. Hence, Hypothesis 1 cannot be rejected by the model. This result is in accordance with Kongaut and Bohlin (2016) for the adoption of smartphones in general. This finding is also in line with a large body of studies analysing the effect of age on PAT adoption (Pierpaoli et al. 2013; Tey and Brindal, 2012).[2] Literature from PAT adoption studies shows that younger farmers are more inclined to use information technologies and therefore are more willing to adopt PAT (D'Antoni et al. 2012). This could also hold true for smartphone adoption in agriculture. Younger farmers may have a higher interest

[2] It should be noted that there also studies that find a positive, statistically significant effect (Isgin et al. 2008) or no statistically significant effect (Daberkow and McBride 2003) of age on PAT adoption.

in testing and using smartphone technology. Furthermore, Tamirat et al. (2018) noted that younger famers have less farming experience. Therefore, younger farmers may be more willing to be assisted by agriculture-related smartphone apps in decision making. Moreover, smartphone adoption could also assist younger farmers with less experience in working with PAT.

According to Gerpott et al. (2013b), the skills to work with information technologies and smartphones are likely to be better among younger adults in general. Adoption of a smartphone may require learning new skills, which can be time consuming, especially for older farmers, who are less likely to be familiar with digital ICT (Rose et al. 2016). This is in line with the results from Roberts et al. (2004) for the adoption of PAT. The authors argued that older farmers were less willing to face learning curves than younger farmers. Hence, older farmers may be less willing to learn how to work with smartphones and how to integrate smartphones successfully into their farm business. Furthermore, older farmers appeared to be less keen to change habits and were therefore less willing to adopt PAT (Tamirat et al. 2018). Rose et al. (2016) suggested the same for the adoption of digital technologies, which could also hold true for the adoption of smartphones in agriculture. Lastly, older farmers have a shorter time horizon for bearing high learning costs associated with the usage of computer technology (Batte et al. 1990) or PAT (Larson et al. 2008), which could also hold true for the adoption of smartphones in agriculture. Hence, older farmers are less likely to adopt a smartphone than younger farmers.

H2 More highly-educated farmers are more likely to own a smartphone.

The model shows evidence in support of Hypothesis 2. Education was integrated in the model as a dummy variable taking a value of 1 if the farmer had a university degree and 0 otherwise. The coefficient has the expected positive sign and the marginal effect is statistically significant. The results indicate that farmers holding a university degree have a 7.10% higher chance of owning a smartphone. Therefore, Hypothesis 2 cannot be rejected. This result parallels the results of smartphone (Poushter 2016) and PAT (Roberts et al. 2004; Walton et al. 2008) adoption studies. Education enables a farmer to process information regarding new technologies more easily (Poolsawas and Napasintuwong 2013). Likewise, a higher education level provides skills and knowledge to adopt and use PAT (Paustian and Theuvsen 2017). In line with this, Tey and Brindal (2012) suggested for the positive effect of education on PAT adoption that more highly-educated farmers have higher analytical skills, which are needed to analyse the amount of data gathered by PAT. It can therefore be expected, that more highly-educated farmers have the sufficient human capital to work properly with smartphones. However, it can be assumed that smartphones are less complex in use than PAT. The results could also originate from the fact that more highly-educated farmers may also have a greater demand for information in decision making (Carrer et al. 2017). Therefore, these farmers could benefit more from the several functions with respect to data collection or data processing of a smartphone. Along the same lines, information on market prices, weeds and pests could be better utilized by highly-educated farmers for decision making. Moreover, more highly-educated farmers could also take more advantage of the information gathered by WS networks (Abdullahi et al. 2015; Kamilaris and Pitsillides 2016; Mesas-Carrascosa et al. 2015). To conclude, more highly-educated farmers have higher chances of adopting a smartphone.

H3 Male farmers are more likely to own a smartphone.

The model provides no support for Hypothesis 3. Gender of the farmer was included as a dummy variable taking a value of 1 if the farmer was male and 0 otherwise. The coefficient has the expected positive sign, but the marginal effect is not statistically significant. The results imply that farmers' gender plays no role in smartphone adoption in agriculture. Therefore, Hypothesis 3 can be rejected.[3] However, this is in line with the results of Kongaut and Bohlin (2016) as well as Puspitasari and Ishii (2016), who investigated determinants of smartphone adoption in general and found no statistically significant effect of gender on the adoption decision. Gerpott et al. (2013a) concluded in their study that the gender divide in digital media is narrowing fast and this might explain the fact that no statistically significant effect of gender on smartphone adoption in agriculture was found. Hence, male and female farmers have equal chances of adopting a smartphone.

H4 Computer literacy increases the probability that farmers own a smartphone.

The model provides evidence to support Hypothesis 4. Computer literacy was integrated as two dummy variables for owing a laptop or a PC in the model. The dummy variables were 1 if a farmer uses a laptop or a PC and zero otherwise. The coefficients have the expected positive signs and the marginal effects are statistically significant. The results indicate that farmers' computer literacy increases the probability of owning a smartphone by 20.90% if the farmer owns a laptop and by 14.40% if the farmer owns a computer. Hence, Hypothesis 4 cannot be rejected. Puspitasari and Ishii (2016) found the same relationship between ownership of computers with internet access and smartphone adoption for Indonesian citizens. With respect to the adoption of PAT, Daberkow and McBride (2003) as well as Paxton et al. (2011) also found a positive link between computer literacy and PAT adoption. The literature suggests on the one hand, that farmers with computer literacy have already gained some knowledge and skills with respect to digital operations and are therefore more likely to be PAT adopters (Tey and Brindal 2012). This could also hold true for the adoption of smartphones in agriculture since modern smartphones are akin to modern laptops with internet access (Wang et al. 2014). On the other hand, Larson et al. (2008) emphasized that a computing device is necessary to process collected data in PAT. As shown by Fulton and Port (2018) and the results of Table 2, smartphones can be used by farmers for field and herd management data collection and intermediate data storage. The collected data can then be transferred to the computer or laptop and analysed for decision making. Furthermore, smartphones can facilitate data transfer between wireless sensor networks and computers (Mesas-Carrascosa et al. 2015; Peres et al. 2011). In summation, farmers' computer literacy increases the likelihood of smartphone adoption in agriculture.

H5 Self-reported innovativeness of farmers increases the probability that farmers own a smartphone.

The model shows evidence to support Hypothesis 5. Innovativeness was measured using an equally spaced 5-point Likert scale. The coefficient has the expected positive sign and the marginal effect is statistically significant. A one point increase on the scale increased the chances of smartphone adoption by 5.30%. Thus, Hypothesis 5 cannot be rejected.

[3] The reader should be cautioned that the number of female farmers in the sample is small which could limit the resilience of the statistical results.

In general, innovative individuals adopt new technology and products more quickly than others. This finding is therefore in line with Aubert et al. (2012) who found that farmers' innovativeness significantly increased the adoption of PAT. Cavallo et al. (2014) observed the same for the adoption of technological innovations for agricultural tractors. They concluded that innovative farmers in general have a more positive attitude towards new technologies. Furthermore, these farmers can assist the further development of technologies due to their high interest in innovations (Cavallo et al. 2014). In sum, innovative farmers are more likely to be smartphone owners.

H6 Farmers from smaller farms are less likely to own a smartphone.

The model shows evidence to support Hypothesis 6. The coefficients of the farm size classes 1 to 3 have the expected negative signs and the marginal effects are statistically significant. The results indicate that farmers operating farms with more than 200 hectares of arable land are more likely to be smartphone owners than farmers operating smaller farms. For instance, farmers cultivating 20 to 50 hectares of arable land are 18.20% less likely to be smartphone owners compared to farmers operating farms with more than 200 hectares of arable land. Hence, Hypothesis 6 cannot be rejected. Gloy and Akridge (2000) suggested that larger farms were better able to recover the cost of computer adoption. The same was suggested for the adoption of PAT (Daberkow and McBride 2003; Lambert et al. 2014). These suggestions mostly follow from considerations of economies of scale in connection to the adoption decision. Compared to computers and PAT, smartphones can be less costly (Pongnumkul et al. 2015). Hence, it can be expected that the positive relationship might not be due to economies of scale. Nevertheless, since increasing farm size also increases the adoption of PAT, it can be assumed that farmers are therefore more willing to adopt a smartphone, since smartphones can facilitate the use of data-driven PAT.

However, Baker (1992) proposed that larger farms have a relatively higher degree of organizational complexity. Furthermore, Mishra et al. (2009) pointed out that farmers from larger farms have a higher demand for information for decision making. Hence, a positive effect of farm size on smartphone adoption is also conceivable since farm operators from larger farms may take greater advantage of several smartphone functions and apps e.g. information gathering for management purposes as well as data collection and analysis (see Table 2). Thus, smartphones can be utilized to facilitate organisation of the farm. In line with this, larger farms can be expected to have a larger number of employees. Consequently, farm operators can use messenger services on smartphones to keep in contact with their employees for organizational purposes (Fecke et al. 2018). This is also in accordance with the results in Table 2. In summary, farmers from small farms are less likely to be smartphone owners.

H7 Farmers from a more diversified farm are more likely to own a smartphone.

The model shows no evidence to support Hypothesis 7. The coefficient for farm diversification has not the expected positive sign and the marginal effect is not statistically significant. This result implies that farm diversification plays no role in smartphone adoption. Hence, Hypothesis 7 has to be rejected. This result is congruent to the studies of Walton et al. (2008) for the adoption of PAT. In addition, Amponsah (1995) observed the same for computer adoption in agriculture. Mishra and Park (2005) suggested that more diversified farmers face more diversified decisions and are therefore more likely to be frequent internet users for information gathering. Therefore, it was expected that operators of more diversified farms could also benefit more from smartphones. However, less-diversified farms can also benefit from smartphones and their several functions and apps. For instance, an arable farmer can install and integrate several apps with different functions just for crop protection. In general, smartphones and information provided by smartphones can be valuable for all types of farmers, for instance, access to information with respect to market data and prices (Table 2). In conclusion, farm diversification has no effect on smartphone adoption.

H8 Location of the farm in the southern region of Germany has a statistically significant negative effect on smartphone adoption.

The model shows evidence to support Hypothesis 8. The coefficients have positive signs and the marginal effects for the region west and north are statistically significant. The results indicate that farmers operating farms in the region south are less likely to be smartphone owners compared to farmers residing in the region west and north of Germany. Farmers residing in the region south are 16.60% less likely to be smartphone owners than farmers living in the region west and 10.90% less likely to be smartphone owners than farmers living in the region north, respectively. No statistically significant difference was found between farmers in the region east and south. Hence, Hypothesis 8 cannot be fully rejected. This is in accordance with the results of Paxton et al. (2011) for the adoption of PAT. The authors attributed their findings to differences in climatic, soil and topographic conditions. For Germany, it can be assumed that these differences might not be so notably strong and decisive as they are in the United States of America. Reichardt and Jürgens (2009) showed that most farms using PAT are located in eastern region of Germany due that fact that farms in this region are larger, and therefore considerations of economies of scale play an important role. As shown before, smartphones are less costly than computers and PAT and therefore considerations of economies of scale might not be so important. However, Hennessy et al. (2016) pointed out that location of the farm can be seen as a proxy for internet coverage and speed. Since some smartphone apps and the transfer of data from PAT to smartphones rely on mobile internet coverage and speed, the findings could be interpreted as a result of insufficient mobile internet speed and coverage. Data from TÜV Rheinland (2017, see Table 4 in the "Appendix") show that mobile internet coverage and speed is relatively less developed in the southern parts of Germany compared to the rest. Thus, farmers located in this region may hesitate to adopt a smartphone since they cannot fully utilize all functions due to missing mobile internet speed. This was also taken in consideration by Dehnen-Schmutz et al. (2016) as a reason for farmers' non-adoption of smartphones and by Rose et al. (2016) for not using digital decision support tools. Lastly, cultural difference between the regions could also be a reason for the observed adoption patterns. For instance, farmers in the southern region of Germany could be less open to new technologies and therefore not willing to adopt a smartphone. However, this was not explicitly tested in this study, but it can be concluded that location plays a role for farmers' smartphone adoption decisions.

Concluding remarks

Smartphones can be used for several business operations in agriculture. Furthermore, smartphones, with their built-in sensors and installable apps, can replicate PAT to a certain extent at lower cost and can also be used as a complement to PAT. Moreover, it was expected that smartphone adoption differs from PAT adoption patterns, despite the fact that these technologies share some characteristics. Until now, there has been no study investigating smartphone adoption and usage by farmers. Against this background, this study provides insights into smartphone adoption and usage in German agriculture. A representative dataset in terms of farmer age, farm size and diversification as well as regional distribution across the study area was analysed by a binominal logit model to identify key factors influencing smartphone adoption. The tested hypotheses relating to the factors influencing farmers' smartphone adoption were derived by referring to the literature in the field of PAT, computer and internet adoption in agriculture as well as smartphone adoption in general. The results confirmed the hypotheses that education and farm size have a positive effect on smartphone adoption. Age has a negative effect on smartphone adoption. Farm location in the southern part of Germany has a negative effect on smartphone adoption compared to farms located in the region west and north. Furthermore farmers' self-reported innovativeness and computer literacy also positively affected smartphone adoption. No effect was found for farm diversification and gender. In summary, most of the factors which were hypothesized to be influential did in fact significantly affect smartphone adoption. Despite the fact that smartphone adoption patterns were expected to be different from factors affecting PAT adoption, the results show similarities for reasons which were elaborated in depth. Furthermore, the study gives empirical justification to previous anecdotal evidence about factors affecting smartphone adoption expected from literature dealing with innovation adoption in agriculture in general. Thus, this study provides insights which could be valuable to policy makers as well as developers of smartphone apps and providers of PAT, farm equipment and services that integrate with smartphones.

Developers of smartphone apps could use these results of the reported current usage of smartphone apps with specific functions to guide further development. For instance, smartphone apps assisting farmers in livestock farming are less reported to be available and used. This could either be a problem of a lack of adequate apps which are offered to farmers or the offered apps do not meet farmers' needs. For providers of smartphone apps or PAT that integrate with smartphones, the study provides insights into the characteristics of the target groups which are most likely to be the adopters of smartphones. According to the results from this study and the literature, the target group shows similarities to farmers which are most likely to adopt PAT. Young, well-educated farmers operating larger farms should therefore be addressed through marketing activities. Hence, marketing efforts towards older farmers from smaller farms will be less fruitful. Furthermore, marketing activities or sellers of PAT that have the possibility to integrate smartphones could explicitly highlight this feature for the target group.

As already mentioned, higher education among farmers has a positive effect on the adoption of smartphones. While it may be obvious that there is no public interest in directly promoting smartphone adoption in agriculture, these results are of relevance for agricultural education in terms of digitalisation in general. Public education for farmers on digitalisation, which has also recently been encouraged by the Federal Ministry of Agriculture (2016) in Germany, should also consider smartphones and their potential to assist farmers in the use of PAT. Increasing awareness of farmers around available technologies could also increase adoption and therefore meet public interests, for instance reducing negative environmental effects through the use of crop protection apps or the use of PAT in combination with smartphones. Furthermore, increasing awareness and ultimately adoption is of interest for the providers and developers of apps since with higher adoption rates they can collect more information for further improvement of smartphone apps to meet farmers' needs.

Since the location plays a role in smartphone adoption, the results suggest that mobile internet coverage could be a barrier to smartphone adoption. Policy makers are clearly advised to put more emphasis on the expansion of mobile and fixed broadband coverage in rural areas. While this is no new demand for policy makers, this study substantiated the demand of German farmers for faster internet services. Smartphones can assist farmers in using PAT, and better mobile internet coverage as a possible promoter of smartphone adoption could also facilitate the adoption of PAT. In general, the internet has become more and more important for PAT (Khanna and Kaur 2019). For further research it could be therefore of interest if (mobile) internet coverage and especially farmers' satisfaction with the provision of internet services is a factor for PAT and smartphone adoption. Likewise, it should be investigated if cultural differences, for instance, with respect to openness to new technologies could explain possible different adoption patters between regions of interest. In line with that, further psycho-social constructs should be considered, for instance, the perceived learning costs or perceived benefit of complementing smartphones and PAT in practical use. Lastly, the willingness-to-pay for smartphones and apps as well as satisfaction with existing apps could be investigated, which could be fruitful for developers and providers of smartphone apps.

Appendix

See Table 4.

Table 4 Mobile broadband (LTE, UMTS) coverage for rural areas and households divided by the federal states and the regions in Germany

Region	Federal state	% of rural households in Germany				% of the rural area in Germany			
		UMTS	Mean[a]	LTE	Mean[a]	UMTS	Mean[a]	LTE	Mean[a]
North	Schleswig–Holstein	58	*61*	89	*89*	65	*56*	93	*89*
	Lower Saxony	66		91		54		88	
	Mecklenburg Western Pomerania	60		88		49		87	
West	North Rhine-Westphalia	77	*70*	89	*88*	61	*58*	82	*84*
	Hesse	65		88		47		83	
	Rhineland Palatinate	52		80		44		74	
	Saarland	87		95		80		96	
South	Baden-Württemberg	51	*57*	81	*84*	33	*40*	73	*77*
	Bavaria	62		88		48		81	
East	Brandenburg	63	*58*	89	*90*	42	*47*	83	*86*
	Saxony	56		88		50		86	
	Saxony-Anhalt	64		92		49		90	
	Thuringia	50		88		47		88	

[a]Mean of the region

Source: Authors' illustration and calculation based on TÜV Rheinland (2017)

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