Investigating the adoption of smartphone apps in crop protection

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Abstract: Based on an online survey of 207 German farmers conducted in 2019, we investigated farmers' adoption decision for crop protection smartphone apps based on the Unified Theory of Acceptance and Use of Technology (UTAUT) framework applying partial least squares equation modelling and a binary logit model. Descriptive results show that 95 % of the surveyed farmers use a smartphone, but only 71 % use a crop protection smartphone app. Apps providing information about weather, pest scouting and infestations forecasts are perceived as most useful by the majority of farmers. However, reported use fell short of reported usefulness. All hypotheses of the UTAUT model could be verified. 73 % of the variation in the behavioral intention to use a crop protection smartphone app and 50 % of the variation in the actual adoption is explained by the model.

Keywords: crop protection, partial least squares structural equation modelling, precision agriculture, smartphone, smartphone apps, unified theory of acceptance and use of technology

1 Introduction

To facilitate a more sustainable agricultural intensification, recent research results and agronomic knowledge in form of practical recommendations need to be transferred to the farmers [SK17]. One way to transfer this knowledge is the use of decision support tools (DST) in crop protection of which smartphone based DST, i.e. apps, are one of the most recent category. Apps can assist farmers in identifying weeds, pests and can also serve as aid in the calculation of spray application rates [Bo18]. By guiding a more targeted management strategy, the smartphone based DST have the potential to increase sustainability of agricultural productivity by reducing negative external effects. While the adoption of smartphones in agriculture [Mi19] and the willingness to pay for crop protection apps [Bo18] has been already studied, no study has focused on the initial adoption of crop protection apps. To investigate psychological factors influencing the adoption of crop protection smartphone apps, the unified theory of acceptance and use of technology (UTAUT) framework was applied [Ve03]. Furthermore, it has not been studied yet which app functions are perceived as useful and which are actually used by farmers. However, evaluating usefulness and use simultaneously provides important insights which can direct future development of smartphone based DST in crop protection since it directly shows the contrast between expectations and actual use.

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2 Theoretical framework

This study is based on a modified UTAUT model for the adoption of crop protection smartphone apps. The UTAUT model was developed by Venkatesh et al. [Ve03] as an integrative approach and combines variables from eight distinct theories. In the UTAUT model, performance expectancy (PE) refers to the extent to which an individual believes that the use of a technology facilitates performing a task or improves his or her job performance. Effort expectancy (EE) is defined as the degree of ease an individual associates with using a system [Ve03]. Venkatesh et al. [Ve03] define social influence (SI) as the extent to which an individual believes that important people in their surrounding think that he or she should use a new technology. Facilitating conditions (FC) are characterized as the degree to which an individual perceives that the present technical infrastructure supports the use of the technology in question and has a direct influence on the adoption decision. The four core constructs influence the behavioral intention to use a technology (BI) which ultimately has a positive effect on the actual adoption decision. Furthermore, effects between EE, SI and PE can be expected. These relationships are shown in the following hypotheses and also in Fig. 1.

H1: Performance expectancy of crop protection smartphone apps has a positive effect on the behavioral intention to use crop protection smartphone apps

H2a: Effort expectancy of crop protection smartphone app use has a positive effect on the behavioral intention to use crop protection smartphone apps

H2b: Effort expectancy of crop protection smartphone app use has a positive effect on performance expectancy of crop protection smartphone apps

H3a: Social influence has a positive effect on the behavioral intention to use crop protection smartphone apps

H3b: Social influence has a positive effect on performance expectancy of crop protection smartphone apps

H4a: Facilitating conditions have a positive effect on the adoption decision for crop protection smartphone apps

H4b: Facilitating conditions have a positive effect on the behavioral intention to use crop protection smartphone apps

H5: Behavioral intention to use a crop protection smartphone app has a positive effect on the actual crop protection smartphone app adoption

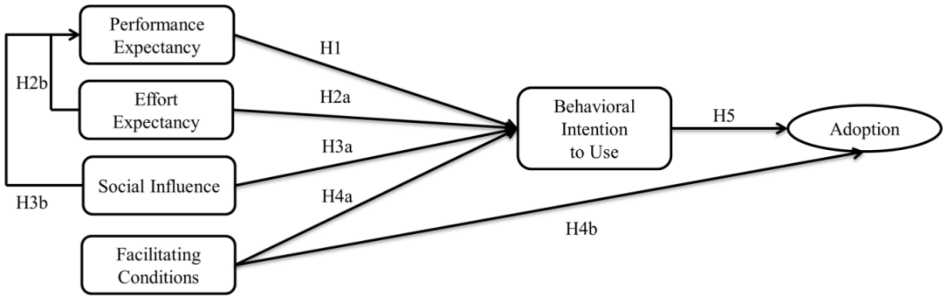

Fig. 1: Proposed modified UTAUT model for the adoption of crop protection smartphone apps

3 Material and methods

An online survey addressed to German farmers was conducted in 2019 using a structured questionnaire. 207 usable records remain after the removal of incomplete surveys. For the estimation of the UTAUT model, participating farmers were asked to evaluate 13 randomized statements using an equally-spaced 5-point Likert scale. The statements serve as the indicators to estimate the constructs of the UTAUT model. Furthermore, farmers had to evaluate which app functions they perceive as useful and which they are actually using. Lastly, farmers were asked to provide socio-demographic and farm related information.

In order to estimate the previously described UTAUT model (see Figure 1), we used structural equation modelling, since we wanted to simultaneously estimate the relationship between constructs as well as the relationship between indicators and constructs. Specifically, we applied partial least squares (PLS) structural equation modelling, as this approach is less restrictive concerning the structure of the data than covariance-based structural equation modelling, which requires normally distributed data. Furthermore, this approach allows the use of constructs with only one or two items. It aims to maximize the explained variance of the endogenous variables. The model consists of two parts: the outer (relationship between indicator and construct) and the inner model (causal relationship between constructs) [Ha16]. Following Hair et al. [Ha16], the evaluation of PLS structural equation modelling results follows two steps. In the first step, the outer model is assessed followed by the assessment of the inner model in the second step. For the assessment of the outer model of the estimated UTAUT model indicator reliability (Loadings), internal consistency reliability (composite reliability, CR), convergent validity (average variance extracted, AVE), and discriminant validity (Heterotrait-Monotrait ratios, HTMT) are tested. For the evaluation of the inner model, explained variance (R^2) and the out-of-sample predictive relevance (Stone-Geisser criterion Q^2) are estimated. Q^2 is estimated by using blindfolding with an omission distance of seven. Since no assumption about the distribution of the data is needed for PLS structural equation modelling, results for hypotheses testing of the path coefficients of the inner model are derived from a re-sample bootstrapping procedure. At least 5,000 subsamples should be applied to generate t-values to allow for hypothesis testing. To avoid biased standard errors by using a dummy variable as an endogenous variable in PLS structural equation modelling, we applied a binary model. For dichotomous variables (1 = adoption of crop protection smartphone app; 0 = non adoption) probit or logit models can be used. Assuming a standard logistic distribution of the error term, we applied a binomial logit model. In specific, the effect of BI and FC on the actual adoption decision (Figure 1) was modelled by implementing the latent factor scores for BI and FC as the independent variables and the dummy variable for the actual adoption decision as the dependent variable in a binary logit model.

The proposed UTAUT model shown in Fig. 1 was estimated using partial least squares structural equation modelling and a logistic regression in SmartPLS 3 [RWB15] and STATA, respectively.

4 Results and discussion

The sample consists of younger (mean = 39.13 years), well-educated farmers (mean = 52 % have a university degree) managing larger farms (mean = 297.90 hectares of arable land) than the German average (53 years old; 12 % with a university degree; 60 hectares of arable land). However, they can be seen as the core group for potential adopters and long-time users of such digital technologies.

Function of crop protection smartphone apps	**Percent reporting considered as useful**	**Percent reporting already in use**
Weather information	0.77	0.83
Pest scouting	0.75	0.52
Infestation forecast	0.64	0.24
Field file/ documentation	0.62	0.39
BBCH determination	0.51	0.34
Product choice	0.51	0.11
Calculation of application quantity of fertilizer	0.44	0.15
Calculation of application quantity of spraying product	0.40	0.10
Recommendations on spray nozzles	0.39	0.08
Planning of crop rotation	0.38	0.07
Manufacturer recommendation	0.27	0.05
Other function	0.08	0.06

Tab. 1: Responses regarding the perceived usefulness and actual use of apps related to various crop protection topics. All figures for the share of farmers who have a smartphone (Variable Smartphone = 1) (n = 198)

With regard to the function of crop protection smartphone apps (Table 1), forecasting, monitoring and documentation features in particular, but also calculation aids and supporting information on product or nozzle choices were perceived as useful. One exception is the result for apps providing weather information. Seventy-seven percent of the farmers reported them as useful, while 83 % stated that they are using them. This result could be explained by the fact that weather apps are installed by default on most smartphones, which also explains the fact that 72 % of the farmers reported the actual use of crop protection smartphone apps, but 83 % use a weather app (Table 1). Furthermore, some farmers might not have considered the weather app explicitly as a crop protection smartphone app. Indicator loadings are above the common cut-off level of 0.7 with the lowest loading for one indicator with 0.709. All indicator loadings are statistically significant. Further proof of the validity of the outer reflective indicators can be found in the values of CR and AVE, which all exceed the cut-off levels of 0.7 and 0.5, respectively. Lastly, all values for the HTMT ratios are below the cut-off level of 0.9 also proving the discriminant validity of the outer model [Ha16]. Therefore, the overall validity of the outer model is proofed.

PLS structural equation model[1)]				
H_0		**Path coefficients**	**t-statistic**[2)]	**Supported H_0?**
PE→BI	H1	0.521***	7.532	Yes
EE→BI	H2a	0.244***	3.959	Yes
EE→PE	H2b	0.633***	14.512	Yes
SI→BI	H3a	0.184**	3.158	Yes
SI→PE	H3b	0.268***	5.195	Yes
FC→BI	H4a	0.008	0.210	No
Binary logit model[3)]				
H_0		**Odds ratio**	**Std. Error**	**Supported H_0?**
FC→Adoption	H4b	1.613*	0.322	Yes
BI→Adoption	H5	5.065***	1.196	Yes

PE = Performance expectancy, EE = Effort expectancy, SI = Social influence, BI = Behavioral intention to use, FC = Facilitating conditions

1) PE (R^2 = 0.654, Q^2 = 0.421), BI (R^2 = 0.732, Q^2 = 0.623)

2) Bootstrap results of 5,000 subsamples

3) Log likelihood = -82.501; LR $chi^2(2)$ = 91.03***; Nagelkerke Pseudo R^2 = 0.50; Pearson $chi^2(72)$ = 75.58, p-value = 0.36; Hosmer-Lemeshow $chi^2(8)$ = 10.74 p-value = 0.21; Correctly classified = 84.54 %

*p-value < 0.05, **p-value < 0.01, ***p-value < 0.001

Tab. 2: Estimation results of the UTAUT model (n = 207)

As shown in Table 2, all hypotheses except for H4a could be verified. The path coefficients PE→BI and EE→PE are statistical significant. Path coefficients can be interpreted as standardized beta coefficients. The results implicate that the apps should provide a clear benefit for the farmer to increase the likelihood of initial uptake. The value of an app for a farmer could be increased with the option to personalize the information provided by the app based on farm location and crop specialization. Furthermore, the positive effect of EE on PE implies that to fully explore the benefits of a crop protection app, this app has to be easy to handle and well structured. An easy to handle app also increases the BI to use such an app as shown with the statistical significant path coefficient EE→BI. The results for the hypotheses testing of H3a und H3b imply that farmers' colleagues have an influence on individual farmers' adoption decision. Young, well-educated farmers are the core group for the adoption of smartphones [Mi19]. Marketing activities of crop protection apps should focus on this core group since they can influence non-adopters in order to widespread adoption. FC have a positive effect on the adoption decision (H4b). As most farmers will use crop protection apps in the field, mobile internet coverage could be barrier for the usage. Thus, developers and providers should consider making the app also functional with an offline modus. As expected, BI has a positive effect on the adoption decision [Ve03].

5 Concluding remarks

This study investigates underlying psychological factors for the adoption of crop protection smartphone apps by applying a UTAUT model to a sample of 207 German farmers collected in 2019. Since adoption fell short of expectations, the statistical significant results of this study provide several implications for developers and providers for further development and improvement of crop protection smartphone apps which can facilitate sustainable intensification in agriculture.

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