Adoption intentions of spot spraying for sustainable weed control – an extended Theory of Planned Behavior approach

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Abstract

Smart farming technologies (SFT) apply agrochemicals in a plant-specific manner which increases feasibility and sustainability of modern farming. However, diffusion lags behind the politically and societally desired levels leaving substantial environmental potential unexploited. Moreover, research on agricultural technology adoption is in imbalance favoring observable farmer and farm-level characteristics over behavioral determinants. In light of increasing political ambitions to foster voluntary uptake towards sustainable intensification, a holistic understanding of drivers including adopters' attitudes and norms is critically needed. In the present study, an extended Theory of Planned Behavior is applied to assess German farmers' intention to adopt spot spraying, a smart weeding technology. While the additional constructs personal innovativeness and moral norms are found to be positive statistically significant antecedents of the attitude towards spot spraying and intention, pro-environmental attitude was found insignificant. Multi-group analysis revealed that farmers with prior SFT experience are slightly younger, better educated and have heightened moral norms and perceived behavioral control regarding adoption intention while unexperienced farmers show a doubled effect of subjective norms on intention. Findings highlight the importance to facilitate and increase access to comprehensive information sources next to channels for innovative farmers to spread and exchange experiences with SFT highlighting both their economic and environmental potential.

Keywords: Sustainable intensification, partial least squares structural equation modelling, multigroup analysis, voluntary technology uptake

JEL code: Q16, Q24, D91

Introduction

In order to meet the rising global food demand (von Braun et al., 2021), strategies in modern agriculture to raise production primarily relied on intensified cultivation of cropland via, e.g., increased use of pesticides and fertilizers associated with biodiversity declines and threats to ecosystem stability (Newbold et al., 2015). However, sustainable intensification, i.e., context-specific and potentially disruptive agricultural system adaptations (Pretty et al., 2018), may mitigate the environmental impacts while allowing for continued food productivity increases (Garnett et al., 2013). Agricultural policy in the developed world has recognized the potential harmful effects of excessive agrochemicals application to human and environmental health. Against this backdrop, the European Union's Farm to Fork strategy, a multi-annual agenda towards more resilient, sustainable, safe and accessible food production, set out to lower the use of pesticides by 50% in all member states until 2030 (European Union, 2020).

Technological innovations in general (Springmann et al., 2018) and smart farming technologies (SFT) in particular are considered key elements to enable the shift towards more eco-efficient ways of farming (Finger et al., 2019; Rübcke von Veltheim & Heise, 2021; Walter et al., 2017). SFT can adapt field operations, formerly uniformly conducted for the whole field, to individual plants introducing several advantages throughout the production process. Precision chemicals application reduces runoff into the environment (Aubert et al., 2012; Wolfert et al., 2017), is associated with lower agricultural greenhouse gas emissions (Balafoutis et al., 2017) and with growing maturity, SFT may even be economically beneficial for farmers due to savings in fuel, chemical and manual labor inputs (Balafoutis et al., 2017; Lowenberg-DeBoer et al., 2020; Weersink et al., 2018). Nevertheless, at present low adoption rates among farmers are observed (Aubert et al., 2012; Barnes et al., 2019a; Paustian & Theuvsen, 2017) suggesting a relevant, yet untapped, environmental potential. Clearly, technology producers next to agricultural and environmental policy makers require strategies to promote the use of SFT, support farmers to work in integrity with the environment and, eventually, enhance the diffusion of sustainable technologies at scale. However, the design and implementation of effective policies necessitate a holistic understanding of the underlying dynamics concerning farmers' attitudes and adoption motives regarding SFT.

This study takes a behavioral perspective to investigate the adoption intention of spot spraying, a sensor-based smart weeding technology (SWT) for precision herbicide application in crop farming. The key objectives of the paper are (1) to derive and test an extension of the Theory of Planned Behavior (TPB) (Ajzen, 1991) using multi-group structural equation modelling and (2) to gain a better understanding of the drivers of German farmers' intentions to adopt SWT and the sources of farmers' preference heterogeneity.

A notable body of research is available on the adoption determinants of digital farming technologies with a focus on observable farmer and farm-level characteristics, i.e., sociodemographic and structural aspects such as age, gender, education level, farm size or biophysical parameters (e.g. Barnes et al., 2019a; Groher et al., 2020; Michels, Fecke et al., 2020; Paustian & Theuvsen, 2017; Tamirat et al., 2017). Results vary depending on study design and context, sampling and estimation strategy, focal technology (group) etc. Similarly, review studies aiming to find systematic patterns among commonly used determinants of sustainable farming practices and technology adoption (e.g. Oca Munguia & Llewellyn, 2020; Pathak et al., 2019; Pierpaoli et al., 2013; Tey & Brindal, 2012) yield inconclusive results, thereby consolidating the presumption of a heterogenous topography of adoption determinants. Next to a lack of unambiguity, the literature on technology adoption has been criticized for underrepresenting behavioral and normative factors associated with adoption of eco-friendly farming technologies (Dessart et al., 2019). However, in light of rising complexity of novel artificially intelligent (AI) farming technology (Sparrow & Howard, 2021) and considering (potential) users' statements regarding difficulties associated with SFT adoption (e.g. Mohr & Kühl, 2021; Reichardt et al., 2009), emphasizing behavioral constructs in the analysis of SFT uptake appears advisable.

This seems all the more warranted when considering that SFT bring about inherently unobservable features. Becoming aware, evaluating and deciding (not) to adopt SFTs are processes unlikely to be purely based on rational thinking. Therefore, scrutinizing farmers' intrinsic motives can enable agricultural extension services, researchers and policy makers alike to develop enabling strategies tailored to the requirements of designated farmer groups. Several contributions based the assessment of (intended) adoption and acceptance on behavioral theories. Using the Reasoned Action Approach, Hüttel et al. (2020) find that for famers' intention to use a precision nitrogen application technology the effect of perceived norms, especially exerted by experienced colleagues, was the single most important determinant of farmers' innovation intention. By contrast, in a study on the acceptance of AI in agriculture (Mohr & Kühl, 2021), the Theory of Planned Behavior and the Technology Acceptance Model were combined to find that farmers personal attitude and perceived behavioral control were most relevant in explaining acceptance with subjective norms being irrelevant. For the case of smart phone app use for farming purposes, Michels, Fecke et al. (2020) adapted the Unified Theory of Acceptance and Use of Technology and found that two attitudinal constructs, effort and performance expectancy next to subjective norms were most relevant in explaining behavioral intention. By comparison, Aubert et al. (2012) combined the Technology Acceptance Model with the Diffusion of Innovations theory to simultaneously assess the role of behavioral aspects and technology attributes for the adoption of a host of precision agriculture tools. Next to the ease of use, perceived usefulness and self-rated innovativeness, they found perceived resources (cf. perceived behavioral control in the TPB) to be important adoption determinants. Lastly, an extended Unified Theory of Acceptance and Use of Technology, applied in Beza et al. (2018) to study the use intentions of SMS services for farming data collection, identified that expected effort, performance and profitability, next to farmers' trust in the service were significant positive determinants of behavioral intention.

This overview shows that over the last decade a stream of literature has emerged investigating factors driving farmers' adoption decision using extended behavioral theories. So far, no study has applied such a framework to investigate the adoption of spot spraying and while attitudinal measures frequently addressed the (expected) relative economic and performance advantage of digital farming technologies, the environmental potential and associated attitudes were usually subsumed under larger thematic constructs (Hüttel et al., 2020; Mohr & Kühl, 2021) or not mentioned at all. Since the European Union's Common Agricultural Policy increasingly emphasizes voluntary uptake of sustainable practices and technologies (European Commission, 2019), characterizing farmers based on underlying behavioral dynamics pertaining to eco-friendly features of farming innovations gains importance (Thomas et al., 2019). This may enable designing a more diversified policy landscape of financial incentives and regulatory measures coupled with voluntary schemes that account for the heterogeneity among farmers. While this may not only spur the uptake of eco-friendly technologies, it may be a more cost-efficient way to foster sustainable intensification in modern farming (Dessart et al., 2019).

The present paper addresses this debate by looking at behavioral adoption intention determinants of spot spraying, a novel weeding technology with a low level of diffusion and awareness among farmers but significant environmental potential. In the baseline model, sufficient in-sample and out-of-sample explanatory power is found, i.e., adoption intention is predicted with adequate precision for the present sample. Subsequently, the model is extended by three behavioral constructs as potential antecedents of the attitude towards spot spraying. Personal innovativeness and moral norms are highly significant, positive determinants of the attitude towards spot spraying, while pro-environmental attitude is found statistically insignificant. Moreover, moral norms have a significant positive effect on adoption intention mediated by the attitude towards spot spraying. A multi-group analysis shows that for those farmers with prior knowledge and experience with SFT perceived behavioral control and moral norms have a stronger impact on adoption intention, while the effect of subjective norms on adoption for this group compared to farmers without prior knowledge and experience is much smaller. Analyzing the two groups in detail reveals that the former is, on average, slightly younger and less experienced, has a higher level of education and a higher share of farmers organized in a corporate farming business, i.e., non-family farms.

Results of this study have implications for future research and policy alike. Besides confirming the suitability of the TPB to assess spot spraying adoption intentions, findings highlight the importance of subjective and moral norms for the adoption intention and attitude towards spot spraying, respectively. Supporting the exchange of information and experiences next to emphasizing the environmental benefits of SFT may help convince hesitant farmers (Hüttel et al., 2020). Tailoring farmer support strategies according to the heterogeneity identified in this sample may accelerate the diffusion of environmentally and societally conducive SFT among innovative, knowledgeable farmers where it is most likely to happen (Dessart et al., 2019). The remainder of this paper is structured as follows. In the next section, research hypotheses based on the TPB and the extension of the framework are derived. This is followed by the description of survey design and sample statistics. Subsequently, the results are presented before the article concludes with a discussion of the limitations and the outlook for future research.

Theoretical framework

The Theory of Planned Behavior (TPB) (Ajzen, 1991) is a psychological framework that draws on three behavioral constructs – attitude, subjective norms and perceived behavioral control – to predict subjects' intention and actual implementation of a certain behavior. The attitude represents the degree to which the behavior under consideration is perceived as desirable, beneficial or useful for the individual, subjective norms represent social influences or pressures affecting the individual regarding the given behavior, and perceived behavioral control represents an individual's own perceived capabilities and control to perform a certain action. More favorable attitude, subjective norms and perceived control over the behavior are assumed to lead to a higher intention towards the behavior in question (Ajzen, 1991). Based on the TPB, the following three hypotheses are formulated:

H1: A favorable attitude towards using spot spraying for weed management has a positive effect on the intention to use spot spraying.

H2: Subjective norms that are in favor of using spot spraying have a positive effect on the intention to use spot spraying for weed management.

H3: A high level of perceived behavioral control with respect to using spot spraying has a positive effect on the intention to use spot spraying.

The TPB has frequently been applied to the context of sustainable agricultural innovations and practices (Sok et al., 2021). Nevertheless, its three constructs may in some cases be insufficient to explain behavior under consideration (Sniehotta et al., 2014). Formulating additional constructs is explicitly considered as an option (Fishbein & Ajzen, 2010) as it may increase model predictive accuracy (Sok et al., 2021). Three additional constructs are suggested to capture the factors relevant for explaining farmers' intention to use spot spraying.

According to Rogers' (1983) seminal Theory of Diffusion of Innovations, individuals who try and implement (technological) innovations at early stages are described as venturous, uncertainty-loving, and keen to gather information on latest technological gadgets which, if evaluated positively, results in a positive attitude towards a particular innovation. Several studies on digital farming technology adoption have used the concept of farmers' innovativeness as an explanatory behavioral measure in different conceptual setups. For example, Michels, Fecke et al. (2020) and Aubert et al. (2012) found a small but positive direct associations between farmers' innovativeness and smart phone ownership and adoption of precision farming tools, respectively. However, a significant effect of personal innovativeness could not be confirmed in Beza et al. (2018) for the case of farmers' intention to use SMS for agricultural services and Barnes et al. (2019a) found innovativeness to be a significant determinant for variable rate nitrogen fertilizer technology only for those farmers who had previously adopted a machine guidance technology. Arguably, although being generally innovative and interested in technological developments, a direct effect on adoption intention of new technologies may not be detectable. When technologies are still at prototype level, potential adopters might delay adoption expecting to see further maturation of the technology which they, in principle, evaluate as beneficial for their farm (Reichardt & Jürgens, 2009). It is, therefore, intuitive to assume that the effect of farmers' innovativeness impacts intended adoption in an indirect way. Mohr and Kühl (2021) find personal innovativeness to be mediated by use attitudes and control believes regarding the acceptance of agricultural AI technologies. These considerations justify hypothesis four:

H4: A high level of **personal innovativeness** has a positive effect on the attitude towards using spot spraying for weed management.

The TPB captures the effect of subjective norms on individuals' intentions but personal norms and values are underrepresented (Ajzen, 1991). According to Dessart et al. (2019), individual environmental concern is a dispositional behavioral determinant influencing all of a farmer's decisions. Potential (environmental) consequences of future decisions are evaluated accordingly such that any action in favor of one's pro-environmental values creates a satisfactory feeling about oneself, a reduced feeling of guilt (Andreoni, 1990), and mitigate cognitive dissonance (Festinger, 2009). Farmers may therefore assess practices or technologies which enable them to act in line with their environmental preferences more positively and subsequently show higher inclination to adopt them. Most identified publications assessing farmers' environmental concerns focus on the adoption of organic farming. For example, Toma and Mathijs (2007) found environmental concern to be a direct antecedent of Romanian farmers' willingness to participate in organic farming programs. Moreover, Läpple (2010) assessed Irish farmers' organic farming adoption behavior according to the timing of adoption and showed that higher environmental concerns were a relevant predictor of adoption, irrespective of being among early or late adopters. As exemplified, most research regarding environmental concerns assumed a direct relationship to adoption behavior finding mostly unambiguous positive effect relationships. However, the present study is concerned with the less researched relation between farmers' environmental attitude and the evaluation of an environmentally beneficial technology. Best (2010) studied the effect of German farmers' environmental concern on opinion towards organic farming pertaining to the subsequent likelihood to adopt it. They find that a favorable environmental attitude is associated with a higher evaluation of organic farming, leading to a higher adoption likelihood. Along these lines, the fifth hypothesis is formulated accordingly.

H5: A favorable **environmental attitude** has a positive effect on the attitude towards using spot spraying for weed management.

In addition, moral norms represent an individual's personal value compass, perceived responsibilities or obligations regarding certain behaviors (Schwartz, 1977). They are based on the evaluation of potential consequences of one's own actions (Arvola et al., 2008) and span a range of behaviors rather than individual actions (Dessart et al., 2019). Since the merits of sustainable farming practices transcend field boundaries in a public good character, moral norms may capture what a *good* farmer ought to do according to her self-image within society. Exemplary empirical studies finding relevant effects of moral norms to determine intended eco-friendly behavior focused on waste reduction (Li et al., 2018; Wang et al., 2020), purchase of electric cars (Wang et al., 2016) or organic food (Thogersen & Olander, 2006). In the agricultural context, Karimi and Saghaleini (2021) found moral norms to indirectly determine the intention to conserve range lands via attitude. Rezaei et al. (2019) found personal norms to be a positive direct determinant of Iranian farmers to aspire to implement integrated pest management and in Bagheri et al. (2019), favorable moral norms significantly reduced Iranian farmers' intention to use pesticides, directly and indirectly. Clearly, depending on the context, moral obligations seem to play a role for behavioral intentions. Therefore, the inclusion of a moral norms construct into the conceptual model is proposed and respective hypotheses are formulated.

$H6_a$: Perceived moral norms that are in favor of using spot spraying have a positive effect the intention to use spot spraying.

$H6_b$: Perceived moral norms that are in favor of using spot spraying have a positive effect on the attitude towards using spot spraying for weed management.

Fig. 1 presets the structural model and the seven related hypotheses regarding farmers' intention to us spot spraying.

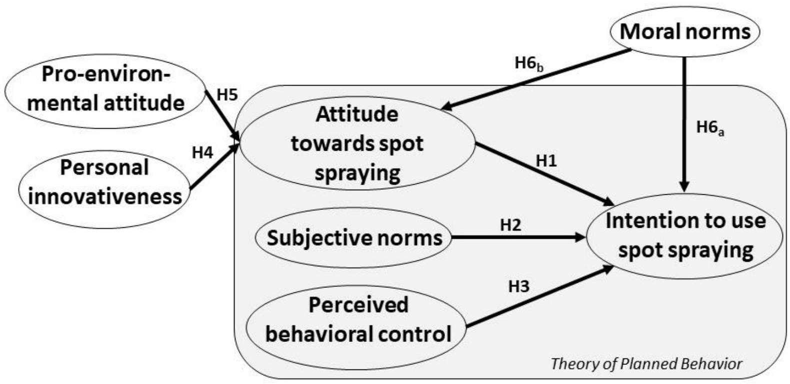

Fig. 1 Adapted research model based on the Theory of Planned Behavior (Ajzen, 1991)

Data

Questionnaire and behavioral constructs

The target group consists of conventional arable crop farmers in Germany. The online survey was distributed via email in several German federal states through multiple channels. The survey was initialized by two questions regarding participants' prior knowledge and use regarding smart farming in general and spot spraying in particular. Subsequently and disregarding if participants indicated prior exposure to spot spraying or not, an informational text about the functionality of spot spraying was given to create a common knowledge background. The next section contained the set of item questions representing the seven latent constructs of the research model. For the formulation of indicator questions, validated scales from previous literature were used in order to guarantee robust construct measurement. Moreover, in adapting the indicators to the context of the study in line with the hypotheses, it was adhered to the principles of construct and scale compatibility whenever possible (Sok et al., 2021). Specifically, the behavior was framed regarding the specific action, time period and context and indicators were operationalized via 7-point Likert scales (Fishbein & Ajzen, 2010). The questionnaire was pretested with 18 members (mostly active farmers) of the farmers representation of North Rhine-Westphalia upon which survey formulations were slightly adapted. The focal behavior referred to farmers' intention to use spot spraying for herbicide-reduced weed management on parts of their own farmland within the next five years (INT) and the attitude construct depicted the extent to which participants perceived spot spraying to be beneficial to their farming business (AttSS). The subjective norms statements addressed the influence of significant professional individuals on participants' spot spraying adoption decision (SN) and the item questions regarding perceived behavioral control covered the aspects of technological and intellectual resources, next to the power of decision (PBC). While pro-environmental attitude addressed farmers' general intrinsic value compass towards the environment (AttEnv), moral norms investigated farmers' self-concept and emotional associations with reduced herbicide application (MN), and personal innovativeness investigated aspects of farmers' self-rated openness to and curiosity about technological innovations (PI). The survey concluded by asking participants a set of questions regarding their sociodemographic and farm background.

Sample

Data acquisition took place between February and April 2022. In order to find a medium-sized effect (Cohen's f^2 of 0.3), an a-priori power analysis assuming a power level of 90%, a significance level of 5%, and a set of 7 latent with a total of 23 observed (indicator) variables yielded a minimum sample size of 210 observations (Soper, 2023).

The study was started by 713 participants. Participants who did not finish the study (n=332, dropout rate=45,4%) and who refused to consent to the use of their anonymized survey responses (n=3) were filtered out. Since neither chemical usage and therefore nor spot spraying is applicable in organic farming, organic farmers were excluded from the sample (n=45) yielding the final data set of 333 complete observations thereby exceeding the minimum required sample size (Table 1).

Table 1 Sociodemographic and farm characteristics

Variable	Mean/share (SD)
Age	43.3 (11.7) years
Education	58% vocational training, state-approved/master's certificate; 37% bachelor/master degree; 1.5% doctoral degree 3% other
Full-time farming	80%
Family farm	92%
Farm size	
0-5	0.6%
6-10	1.5%
11-20	5.1%
21-50	16%
51-100	29%
101-200	25%
> 200	23%
Experience with smart farming technologies	31%
Knowledge of spot spraying technology	35%

N=333

The authors acknowledge the presence of potential selection bias resulting from the online mode of survey distribution and participation, the selected distribution channels and the topic of the survey which may have been of varying interest to the addressed farmer population. The data set may therefore be considered a convenience sample (cf. Hüttel et al., 2020). With 43.3 years of age, the average participant is approximately ten years below the German average and with 80%, the share of full-time farmers in the sample is about twice as large compared to the underlying population. With 48% participants cultivating 101 hectares or more, the sample overrepresents the German average of 63.2 hectare per farm. This observation becomes even more emphasized by the fact that around 90% of the sample was collected in the federal states of North Rhine-Westphalia, Bavaria, Baden-Wuerttemberg and Lower Saxony where average farm sizes are 43.8, 36.0, 36.6, and 72.7 hectares, respectively. However, with 92% family-owned farms the sample is well representative of the German average (86,7%). Lastly, with about 40% of participants carrying at least a bachelor degree, the sample achieves an above average level of education. In essence, the sample is biased towards younger, well-educated farmers that operate disproportionately large farms. Together with the fact that 31% (35%) of participants have prior knowledge of smart farming technologies (spot spraying in particular), the sample renders itself especially interesting to study the adoption intention of innovative venturous farmers (Tamirat et al., 2017).

Analysis

For the analysis of this study, structural equation modeling (SEM) was applied, an estimation approach for simultaneous estimation of multiple regressions to assess the effects of several exogenous (independent) variables on a set of endogenous (dependent) variables (Hair et al., 2019). Specifically, partial least squares (PLS) SEM was used, a non-parametric variance-based estimation strategy that maximizes the explained variance in endogenous variables (Hair, Hult et al., 2017). PLS allows researchers to extend existing theoretical frameworks and derive model-based predictions (Hair, Matthews et al., 2017). This renders this method particularly useful to formulate recommendations for practitioners (Hair et al., 2021) and since no assumptions regarding the distribution of the data (e.g. normality) need to be met, PLS provides high flexibility (Hair, Hult et al., 2017). In a first step, SEM encompasses the measurement of theoretical constructs (measurement model) among which, in a second step, relationships are estimated (structural model). The constructs used in SEM are latent (unobservable) by nature and are therefore measured indirectly by sets of observable indicators (attitudinal statements) that hold as a proxies for the underlying constructs (Hair, Hult et al., 2017). Reflectively measured constructs are composed of items which are assumed to stem from the same underlying theoretical domain. The items are interchangeable, leaving out one indicator does not substantially change the construct, and the direction of the relationship goes from the construct to the indicators (Hair, Hult et al., 2017). The items of formatively measured constructs are assumed to cover different aspects of the same theoretical field and are not interchangeable. Leaving out one item can substantially change the meaning of the construct and the relationship goes from the items to the constructs (Hair, Hult et al., 2017).

Measurement model evaluation

For the evaluation of the PLS SEM, it was proceeded in two steps as proposed by Hair et al. (2021). First, the measurement model was assessed for a set of reliability and validity criteria followed by the structural model assessment and testing of hypothesis.[1] Reflectively measured constructs were evaluated for indicator reliability, internal consistency reliability, convergent validity and discriminant validity (Hair, Hult et al., 2017). Indicator reliability describes how much of each indicator's variance is captured by its construct with a threshold value for the standardized loadings of >0.708. Internal consistency reliability, the degree to which indicators measuring the same construct are related with each other, was tested via a composite reliability (CR) criterion with a threshold level of 0.7. To assess convergent validity, i.e., the magnitude of variance of each indicator captured by its respective construct, was assessed via the average variance extracted (AVE) with a minimum reference value of 0.5. Finally, to assess whether hypothetical constructs were empirically distinct from one another (discriminant validity) the heterotrait-monotrait ratio was assessed (Henseler et al., 2015) that should be below 0.85. The assessment of the data based on the discussed criteria reveals very high composite reliability values (>0.95) for constructs INT, AttSS, AttEnv and SN suggesting redundancy among items potentially causing undue correlation of items' error terms (Hair et al., 2021). After deleting one

[1] All analysis steps were performed in R using the package "seminr".

item of each problematic construct all discussed reflective measurement model evaluation criteria are met (Table 2 and Table 3).

Table 2 Reflective constructs: descriptive statistics, indicator reliability, internal consistency reliability and convergent validity

Construct	Statement	Mean (SD)	Loading[a]
Intention to adopt spot spraying (CR=0.929, AVE=0.934)			
INT_1	I will try to use spot spraying as a weeding method on parts of the acreage currently under cereal or root crops cultivation within the next five years.	3.34 (1.90)	0.967***
INT_2	I intend to use spot spraying as a weeding method on parts of the acreage currently under cereal or root crops cultivation within the next five years.	3.13 (1.88)	0.966***
Attitude towards spot spraying (CR=0.89, AVE=0.889)			
AttSS_1	I think that the use of a spot spraying technology for weed management can increase profitability of my farm.	4.24 (1.80)	0.934***
AttSS_2	I think that the use of spot spraying technology for weed control can be advantageous for my farm.	4.40 (1.78)	0.952***
Pro-environmental attitude (CR=0.892, AVE=0.81)			
AttEnv_2	Respecting the earth: harmony with other species.	6.00 (1.13)	0.911***
AttEnv_3	Unity with nature: fitting into nature.	5.74 (1.32)	0.898***
AttEnv_4	Protecting the environment: preserving nature.	6.01 (1.97)	0.891***
Subjective norms (CR=0.928, AVE=0.933)			
SN_1	People who are important to me regarding my business decisions on farm think that I should use spot spraying technology.	3.12 (1.75)	0.966***
SN_2	People who influence my business decisions on farm think that I should use spot spraying technology.	3.15 (1.79)	0.966***
Moral norms (CR=0.885, AVE=0.81)			
MN_1	I would feel guilty if I did not try to reduce the applied amounts of herbicides on my fields in order to protect the environment and strengthen biodiversity.	4.47 (1.99)	0.864***
MN_2	When I reduce the amounts of applied herbicides on my fields to protect the environment and strengthen biodiversity I feel like a better farmer.	5.37 (1.68)	0.917***
MN_3	I feel morally obliged to reduce the amounts of applied herbicides on my fields in order to save the environment and strengthen biodiversity.	4.98 (1.88)	0.917***
Personal innovativeness (CR=0.854, AVE=0.692)			
PI_1	I am generally very curious about how new technologies work.	5.89 (1.11)	0.828***
PI_2	I often research information on new technologies (magazines, internet, technology experts etc.).	5.29 (1.48)	0.834***
PI_3	I like to try out/experiment with new technology.	4.95 (1.56)	0.856***
PI_4	I like to be around colleagues who experiment with new technologies.	5.11 (1.51)	0.808***

Threshold values: loadings>0.708, CR>0.7, AVE>05
[a] Significance code: ***p<0.01, **p<0.05, *p<0.1
N=333

Table 3 Reflective constructs: discriminant validity

	AttSS	SN	PI	AttEnv	MN
AttSS					
SN	0.676				
PI	0.296	0.278			
AttEnv	0.204	0.193	0.381		
MN	0.465	0.422	0.315	0.548	
INT	0.701	0.7	0.392	0.263	0.451

Threshold value for HTMT<0.85
AttSS Attitude towards sport spraying, *SN* subjective norms, *PI* personal innovativeness, *AttEnv* pro-environmental attitude *MN* moral norms, *Int* Intention
N=333

To the remaining (formatively measured) construct PBC, similar criteria were applied, i.e., indicator collinearity and the significance and relevance of indicator weight and loadings were evaluated (Hair, Hult et al., 2017). High correlation between indicators of formative constructs increases the standard errors of indicator weights which may cause imprecise or incorrect estimation, and unexpected sign changes thereof (Hair, Hult et al., 2017). This was tested via the variance inflation factors (VIF) for the set of PBC items with acceptable values below 5. Subsequently, indicator weights, loadings and their significance were inspected for relative and absolute item importance. While the VIFs for all PBC items lie within the acceptable range, the weight of two items are insignificant. However, in line with Hair et al. (2021) a subsequent inspection of respective loadings and their significance yielded acceptable results, thus, all PBC items were retained in the data (Table 4).

Table 4 Formative constructs: descriptive statistics, indicator collinearity, weights and loadings

Construct	Statement	Mean (SD)	VIF	Weight[a]	Loading[a]
Perceived behavioral control					
PBC_1	*I have sufficient knowledge and skills to implement spot spraying technology on my farm.*	4.16 (2.05)	1.496	-0.022	0.539***
PBC_2	*The decision to implement spot spraying technology on my farm is under my control.*	5.57 (1.71)	1.085	-0.008	0.227***
PBC_3	*I have sufficient technical resources and time to implement spot spraying technology on my farm.*	3.50 (1.84)	1.486	1.003***	0.988***

Threshold values: VIF<5
[a] Significance code: ***p<0.01, **p<0.05, *p<0.1
N=333

Results of the measurement model evaluation presented above are proof of the reliability and validity of the outer model permitting to proceed with the inner model evaluation.

Structural model evaluation and testing of hypotheses

As the first step in the structural model evaluation, multicollinearity among endogenous variables was checked via the VIFs and a respective threshold level of 5 (Hair, Hult et al., 2017). With all VIFs ranging between 1.148 and 1.719, no issues of multicollinearity are present. Next, the R^2 and Stone-Geisser criterion Q^2 for both endogenous variables were calculated to assess the model's total variance explained (in-sample predictive power) and out-of-sample predictive relevance, respectively (Hair, Hult et al., 2017). The latter was calculated in an iterative blindfolding procedure with an omission distance of ten. With an R^2 of 0.56 on INT, the main inner model has moderate in-sample predictive accuracy and a Q^2 larger than zero (0.468) indicates that the model has relevant out-of-sample predictive power (Hair, Hult et al., 2017), allowing to analyze the structural paths and to test the hypotheses (Table 5). Since the PLS approach does not assume normality of data, a bootstrapping procedure with 10,000 iterations was applied to derive t-values used to investigate significance of standardized beta coefficients (Hair, Hult et al., 2017).

Table 5 Estimation results of the extended TPB model

Path	Hypothesis	Standardized path coefficient[a]	t-statistic[b]	Hypothesis supported
AttSS → INT	H1	0.322***	6.058	Yes
SN → INT	H2	0.345***	5.966	Yes
PBC → INT	H3	0.200***	4.498	Yes
PI → AttSS	H4	0.171***	3.181	Yes
AttEnv → AttSS	H5	-0.066	-1.083	No
MN → INT	$H6_a$	0.094*	6.948	Yes
MN → AttSS	$H6_b$	0.398***	2.258	yes

AttSS Attitude towards sport spraying, *SN* subjective norms, *PI* personal innovativeness, *AttEnv* pro-environmental attitude, *MN* moral norms, *Int* Intention

INT (R^2=0.558, Q^2=0.468), AttSS (R^2=0.196, Q^2=0.175)

[a] Significance code: ***p<0.01, **p<0.05, *p<0.1

[b] Based on bootstrapping procedure with 10,000 resamples

N=333

Significant empirical evidence is found for all pre-registered hypotheses but for H5. Specifically, a statistically highly significant path coefficient (0.322) supports H1 that a positive attitude towards spot spraying is associated with a higher intention to adopt it. Comparable in magnitude (0.345) and significance, favorable subjective norms have a positive effect on adoption intention (H2). Moreover, a significant coefficient of 0.2 supports H3, i.e., higher perceived behavioral control has a positive effect on intention. Thus, all three constructs of the TPB are highly relevant in explaining spot spraying adoption intention in this sample.[2] Additionally, a statistically significant positive relationship between PI and AttSS is found (0.171), i.e., farmers who perceive themselves as more innovative evaluate spot spraying more positively (H4). However, no support is found for hypothesis H5, i.e., higher levels of pro-environmental attitude are not associated with higher attitude towards spot spraying. Both hypotheses regarding moral norms are supported. While the coefficient between MN and INT is relatively small (0.094) but significant at the 10% level ($H6_a$), the path coefficient between MN and AttSS is highly significant. With a magnitude of 0.398, it is more than twice as large as that of PI to AttSS. In addition, the indirect effect of MN on the INT and a potential mediating effect were tested. The indirect effect of MN on INT through AttSS has a magnitude of 0.128 and is highly significant. Considering the statistically significant direct effect of MN on INT ($H6_a$), evidence for complementary mediation via AttSS is found with a total highly significant effect of 0.222.

Exploratory analysis

Following (Beza et al., 2018), multi-group analysis was performed. Specifically, the sample was divided into farmers who had (had no) prior knowledge or experience with SFT (ExpSFT). Subsequently, the research model (Fig. 1) was rerun to identify potential systematic differences in path coefficients. Asterisks in columns two and three in Table 6 indicate the significance of path coefficients for the respective subsample and the p-values in column four indicate the p-values from testing for significant differences between the path coefficients across groups. Analyzing path significances and magnitudes next to R^2 and Q^2 in the subsamples shows that results from the full sample (Table 5) are largely

[2] Supplementary analysis results for the baseline TPB model are available upon request.

reproduced. Comparing subsamples to each other reveals three aspects of interest. First, the effect of SN on INT in group 2 is almost twice as large and highly significant compared to group 1 while, second, the effect of PBC on INT is more than twice as large in group 1 and statistically different. Third, the effect of MN in group 1 is approximately six times larger and statistically highly significant compared to group 2. Moreover, a p-value of 0.01 renders this group difference statistically highly significant.

Table 6 Multi-group analysis based on SFT knowledge indicator variable

Path	Standardized path coefficient[a] Group 1 (ExpSFT=1)	Group 2 (ExpSFT=0)	p-value
AttSS → INT	0.350***	0.312***	0.270
SN → INT	0.231*	0.400***	0.960
PBC → INT	0.301***	0.145**	0.020
PI → AttSS	0.165*	0.123*	0.290
AttEnv → AttSS	-0.096	-0.068	0.610
MN → INT	0.211***	0.035	0.010
MN → AttSS	0.356***	0.445***	0.910
N	103	230	-

AttSS Attitude towards sport spraying, *SN* subjective norms, *PI* personal innovativeness, *AttEnv* pro-environmental attitude, *MN* moral norms, *Int* Intention, *ExpSFT* prior knowledge of/experience with/use of smart farming technology
$INT_{ExpSFT=1}$ (R^2=0.640, Q^2=0.424), $AttSS_{ExpSFT=1}$ (R^2=0.164, Q^2=0.181), $INT_{ExpSFT=0}$ (R^2=0.521, Q^2=0.486), $AttSS_{ExpSFT=0}$ (R^2=0.209, Q^2=0.091)
[a] Significance code for path coefficient of subsamples: ***p<0.01, **p<0.05, *p<0.1

To further characterize farmers with and without prior exposition to SFT, sociodemographic and farm structural variables were examined. On average, farmers with prior SFT experience are slightly younger and have less practical farming experience (p<0.1). Most importantly though, farmers with SFT experience have a larger share of higher secondary and academic degrees indicating an on average significantly (p<0.001) higher level of education. Lastly, among experienced farmers a significantly (p<0.001) larger share is working in a farming business other than a family farm, i.e., a cooperative. In a next step, the grouping variable ExpSFT was assessed econometrically. A probit regression was estimated to examine the association of the set of collected control variables with participants' probability to have acquired prior knowledge or experience with smart farming technologies. Two determinants are statistically significantly associated with ExpSFT. Having acquired higher secondary education and managing a cooperative is associated with increased probability of prior knowledge and experience with SFT of 14,4 and 36.7 percentage points, respectively, thereby confirming the findings from the previous comparison of descriptives across groups.

Discussion

SFT tailor agricultural practices to individual plants which is discussed to be a paradigm shift in modern agriculture (Lindblom et al., 2017) since this has both economic and environmental potential. However, farmers are yet hesitant to adopt SFT leaving this potential widely unexploited. This study assessed adoption intentions of spot spraying, a sustainable weeding technology, in a sample of German crop farmers through a behavioral lens. With sufficient in-sample and out-of-sample predictive power, adoption intention is well explained by the exogenous constructs. Specifically, all baseline model path coefficients are economically and statistically significant thereby reconfirming the adequacy of the TPB for agricultural innovation adoption (cf. Sok et al., 2021). Coefficients of AttSS and especially SN are somewhat larger in magnitude than that of PBC emphasizing that the higher potential users and relevant others evaluate spot spraying the higher the adoption intention will be. Findings for AttSS are in line with previous studies highlighting the importance of the attitude towards a behavior for the cases of integrated pest management (Rezaei et al., 2019), field robots (Rübcke von Veltheim & Heise, 2021) and smart phone app use in farming (Michels, Bonke, & Musshoff, 2020). The AttSS construct consisted of somewhat economically framed statements suggesting that farmers who primarily believe spot spraying to be profitability increasing have higher adoption intentions thereof (cf. Barnes et al., 2019a; Pierpaoli et al., 2013). Similarly, the findings for SN, the strongest direct determinant of INT, reinforce previous research on the adoption of digital farming technology identifying relevant professional others as important influences on intention (Hüttel et al., 2020; Michels, Bonke, & Musshoff, 2020). The results for PBC are backed up by a similar body of literature, however, technical knowhow and being in control of the adoption decision are of minor relevance here. The most relevant item is the availability of sufficient time and technical resources to implement spot spraying (PBC_3) suggesting that operators of farms with higher digitalization standards and staff availability have a higher inclination to adopt sport spraying.

In assessing potential antecedents of AttSS, an insignificant, negative and small effect of AttEnv is surprising. Pro-environmental attitude is assumed a dispositional behavioral determinant, a guiding principle overarching managerial decision (Dessart et al., 2019). This should therefore manifest in higher attitudes towards spot spraying and thereby indirectly raise adoption intention (Best, 2010). It may be that, despite high average values for all AttEnv items (Table 2), farmers in the present sample did not associate spot spraying with the outlined environmental benefits but with a complex innovation which requires the acquisition of new skills and knowledge (cf. Toma et al., 2018). This is supported by the significant, positive effect of PI, i.e., more innovative farmers evaluate spot spraying more positively. This points to the importance of access and options to communicate knowledge and experiences with SFT (Mohr & Kühl, 2021). Lastly, the effect of MN on AttSS is twice as large compared to PI. As for AttEnv, moral concerns are assumed to encompass farmers behavior more generally (Dessart et al., 2019), i.e., farmers who feel strong moral obligations to behave in certain ways show higher tendencies in expedient attitudes and behaviors. Finding significant direct and indirect effects of MN on INT yield evidence for this connection in the present sample.

In addition to the direct effect of farmers' innovativeness and more positive evaluations of spot spraying, multi-group analysis based on prior knowledge and experience with SFT, reveals interesting details. Most importantly, for knowledgeable farmers the coefficients of perceived behavioral control, attitude towards spot spraying and especially moral norms are more pronounced. This supports the notion that access to information sources strengthens farmers' opinions of and confidence to use novel technologies (Toma et al., 2018) and may heighten farmers perceived ease of using digital technologies (Aubert et al., 2012). Moreover, the significant direct effect of MN suggests that farmers consider spot spraying technology a viable option to comply with their moral obligation to reduce herbicide application on their land for wider environmental benefits. By contrast, the effect of SN on INT is almost twice as large for farmers without prior exposure to SFT highlighting the relative impact of colleagues' opinions for the adoption intention of unfamiliar technologies. Subsequent inspection of sociodemographic characteristics showed that individuals with SFT experience are slightly younger and well-educated operators, a finding backed up by antecedent literature (e.g. Aubert et al., 2012; Kutter et al., 2011). Farmers with higher (academic) education are more experienced with using and synthesizing multiple digital information sources (Reichardt & Jürgens, 2009) which translates in higher digital literacy, a relevant skill when familiarizing with new farming technology (Pierpaoli et al., 2013). Moreover, higher levels of education lead to an improved understanding of the environmental impacts of agrochemical usage which may in part explain the pronounced effect of MN on INT in this subsample. Lastly, knowledgeable farmers originated from a slightly higher share of corporately organized businesses. This is also reflected in the stronger coefficient of PBC which was mainly determined by more abundant technical and time resources.

Findings of this study have several implications for stakeholders inside and outside of policy as they contribute to the debate of exploiting behavioral insights to bolsters the voluntary uptake of sustainable farming technologies. To form an opinion and the subsequent adoption decision of specific SFT, farmers require easy access to useful and trustworthy information sources (Toma et al., 2018). Potential reservations about SFT caused by a lack of knowledge or concerns about system complexity may be reduced through governmental informational campaigns, private consultations and distribution of knowledge via farmer unions and agricultural chambers to emphasize not only the anticipated benefits to profitability but also to reinforce the association of SFT with their environmental benefits due to high chemical savings (Kutter et al., 2011). This may spark the interest of a wider group of potential adopters. Moreover, initial investment costs prevent small, less capital abundant farms from experimenting with novel technologies. Supported by governmental subsidies, technology companies could offer trialing periods, trainings and technical support to raise adoption intentions of smaller, less affluent farming businesses (Barnes et al., 2019b). Additionally, arrangements among adjacent farmers to collectively invest in and share SFT could further help to overcome financial barriers, promote accumulation and exchange of experiences (Blasch et al., 2020) and utilize the full capacity of the technologies. This could create a collaborative atmosphere in which social learning regarding pro-environmental behavior occurs among like-minded farmers leading to higher inclination towards voluntary adoption (Dessart et al., 2019). Lastly, identifying especially innovative young farmers, as was done here, may motivate the implementation of spatially coordinated policy schemes. Specifically, including farmers in agri-environmental governance tasks on the local level can increase cooperation among farmers with respect to sustainable land management practices in a bottom-up approach (Westerink et al., 2017). If combined with financial incentives payed conditional upon reaching a minimum collective engagement in a given area (Kuhfuss et al., 2016), more farmers may voluntarily try SFT.

Conclusion and outlook

SFT are complex to use and to implement. Their adoption may fundamentally alter managerial processes on farm and it appears all the more timely to develop a holistic understanding of innovation drivers and barriers (Aubert et al., 2012). This study highlights the impact of the opinions of farmers' professional environment and the personal moral compass on forming the adoption intention and respective attitude towards spot spraying. Facilitated access to multiple channels of information about the economic and environmental potential complemented with government-funded educational campaigns demonstrating the implementation and handling of SFT could raise positive perceptions towards SFT. Moreover, led by well-educated, young and innovative operators low-threshold options to exchange experiences and independently experiment and share innovations on communal level may help to convince more farmers that SFT are a viable option for technology-based sustainable intensification of modern agricultural production.

In light of several limitations in this study, recommendations for future research are proposed. The proposed model extensions did not substantially increase the predictive power of the baseline TPB. However, the relative importance of determinants of the attitude towards spot spraying could be identified with the effect of moral norms being more than twice as large as personal innovativeness. Since there exists no perfect behavioral model, future studies should continue to test model extensions to adequately depict specific adoption contexts. Moreover, adoption of SFT is no one-time decision but occurs in consecutive steps (Aubert et al., 2012; Barnes et al., 2019a) or bundles (Miller et al., 2019). Future behavioral research should consider this continuum of digitalization and should continue to control for farmers' prior experience with SFT to and technological status quo. Using subjective attitudinal measures limits the generalizability of findings. However, since this research is motivated by a lack of behavioral insights in the SFT adoption literature and application thereof in respective policy, this aspect represents a contribution. Moreover, despite concerns of selection bias inherent to the non-representative convenience sample, survey participants may represent an innovative farmer cohort of curious, venturous early adopters (Rogers, 1983) among which SFT adoption is most likely to happen. As discussed, when addressed with enabling policy strategies, they may act as role models for technology-based ways of sustainable farming, raise local awareness and accelerate the diffusion of SFT within their professional environment (Blasch et al., 2020). Regarding the identification and operationalization of constructs of behavioral constructs, it was relied on theoretical and empirical literature. Future studies should conduct focus group discussions and pilot studies to capture and pretest the relevance of additional items within behavioral constructs or additional dimensions of the wider adoption context (Sok et al., 2021). In this vein, perceived technological complexities and agricultural policy barriers (Kernecker et al., 2020; Reichardt & Jürgens, 2009) could be implemented in comprehensive behavioral models. As SFT are increasingly commercially available and adopted, specific characteristics become observable. Although it was outside the scope of the present study, future work should assess the interplay of more specific attributes and behavioral determinants, and further assess how adoption intentions manifest in actual, i.e., observed behavior. This may yield an additional starting point for policy development and eventually lower the entry barriers for farmers with favorable attitudes to try out new smart technologies.

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Conflicts of interest

The authors declare that they have no financial or non-financial conflicts of interest.

Compliance with ethical standards

This study involved human participants. Prior to data collection, ethical clearance was granted by the ethical board of the Centre for Development Research (ZEF) at University of Bonn. The approved ethical clearance form is available upon request with the corresponding author.

References

Ajzen, I. (1991) The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Andreoni, J. (1990) Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving. *The Economic Journal*, *100*(401), 464–477.

Arvola, A., Vassallo, M., Dean, M., Lampila, P., Saba, A., Lähteenmäki, L., & Shepherd, R. (2008) Predicting intentions to purchase organic food: The role of affective and moral attitudes in the Theory of Planned Behaviour. *Appetite*, *50*(2-3), 443–454. https://doi.org/10.1016/j.appet.2007.09.010

Aubert, B. A., Schroeder, A., & Grimaudo, J. (2012) IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. *Decision Support Systems*, *54*, 510–520. https://doi.org/10.1016/j.dss.2012.07.002

Bagheri, A., Bondori, A., Allahyari, M. S., & Damalas, C. A. (2019) Modeling farmers' intention to use pesticides: An expanded version of the theory of planned behavior. *Journal of Environmental Management*, *248*, 109291. https://doi.org/10.1016/j.jenvman.2019.109291

Balafoutis, A., Beck, B., Fountas, S., Vangeyte, J., Wal, T., Soto, I., Gómez-Barbero, M., Barnes, A. P., & Eory, V. (2017) Precision Agriculture Technologies Positively Contributing to GHG Emissions Mitigation, Farm Productivity and Economics. *Sustainability*, *9*. https://doi.org/10.3390/su9081339

Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., & Gómez-Barbero, M. (2019a) Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. *Land Use Policy*, *80*, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004

Barnes, A. P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., & Gómez-Barbero, M. (2019b) Influencing factors and incentives on the intention to adopt precision agricultural technologies within arable farming systems. *Environmental Science and Policy*, *93*, 66–74. https://doi.org/10.1016/j.envsci.2018.12.014

Best, H. (2010) Environmental Concern and the Adoption of Organic Agriculture. *Society & Natural Resources*, *23*(5), 451–468. https://doi.org/10.1080/08941920802178206

Beza, E., Reidsma, P., Poortvliet, P. M., Belay, M. M., Bijen, B. S., & Kooistra, L. (2018) Exploring farmers' intentions to adopt mobile Short Message Service (SMS) for citizen science in agriculture. *Computers and Electronics in Agriculture*, *151*, 295–310. https://doi.org/10.1016/j.compag.2018.06.015

Blasch, J., van der Kroon, B., van Beukering, P., Munster, R., Fabiani, S., Nino, P., & Vanino, S. (2020) Farmer preferences for adopting precision farming technologies: a case study from Italy. *European Review of Agricultural Economics*, *49*(1), 33–81. https://doi.org/10.1093/erae/jbaa031

Dessart, F. J., Barreiro-Hurlé, J., & van Bavel, R. (2019) Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics*, *46*(3), 417–471. https://doi.org/10.1093/erae/jbz019

European Commission. (2019). *The post-2020 Common Agricultural Policy: Environmental Benefits and Simplification.* DG Agriculture and Rural Development. https://agriculture.ec.europa.eu/system/files/2021-01/cap-post-2020-environ-benefits-simplification_en_0.pdf

European Union. (2020). *Farm to Fork Strategy: For a fair, healthy and environmentally-friendly food system*. https://food.ec.europa.eu/system/files/2020-05/f2f_action-plan_2020_strategy-info_en.pdf

Festinger, L. (2009) *A theory of cognitive dissonance* (Renewed 1985 by author). Stanford, Calif.: Stanford University Press.

Finger, R., Swinton, S. M., El Benni, N., & Walter, A. (2019) Precision Farming at the Nexus of Agricultural Production and the Environment. *Annual Review of Resource Economics*, *11*(1), 313–335. https://doi.org/10.1146/annurev-resource-100518-093929

Fishbein, M., & Ajzen, I. (2010) *Predicting and changing behavior: The reasoned action approach*. New York: Psychology Press.

Garnett, T., Appleby, M. C., Balmford, A., Bateman, I. J., Benton, T. G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P. K., Toulmin, C., Vermeulen, S. J., & Godfray, H. C. J. (2013) Sustainable intensification in agriculture: Premises and policies. *Science*, *341*(6141), 33–34. https://doi.org/10.1126/science.1234485

Groher, T., Heitkämper, K., Walter, A., Liebisch, F., & Umstätter, C. (2020) Status quo of adoption of precision agriculture enabling technologies in Swiss plant production. *Precision Agriculture*.

Hair, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017) PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123.

Hair, J. F., Blacl, W., C., Babin, B., J., & Anderson, R., E. (2019) *Multivariate data analysis* (Eighth edition). Andover Hampshire, United Kingdom: Cengage Learning.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017) *A primer on partial least squares structural equation modeling (PLS-SEM)* (Second edition). Los Angeles, USA: Sage Publications, Inc.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021) *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-80519-7

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hüttel, S., Leuchten, M.-T., & Leyer, M. (2020) The Importance of Social Norm on Adopting Sustainable Digital Fertilisation Methods. *Organization & Environment*, *35*(1), 79–102. https://doi.org/10.1177/1086026620929074

Karimi, S., & Saghaleini, A. (2021) Factors influencing ranchers' intentions to conserve rangelands through an extended theory of planned behavior. *Global Ecology and Conservation*, *26*, e01513. https://doi.org/10.1016/j.gecco.2021.e01513

Kernecker, M., Knierim, A., Wurbs, A., Kraus, T., & Borges, F. (2020) Experience versus expectation: farmers' perceptions of smart farming technologies for cropping systems across Europe. *Precision Agriculture*, *21*(1), 34–50. https://doi.org/10.1007/s11119-019-09651-z

Kuhfuss, L., Préget, R., Thoyer, S., & Hanley, N. (2016) Nudging farmers to enrol land into agri-environmental schemes: the role of a collective bonus. *European Review of Agricultural Economics*, *43*(4), 609–636. https://doi.org/10.1093/erae/jbv031

Kutter, T., Tiemann, S., Siebert, R., & Fountas, S. (2011) The role of communication and co-operation in the adoption of precision farming. *Precision Agriculture*, *12*(1), 2–17. https://doi.org/10.1007/s11119-009-9150-0

Läpple, D. (2010) Adoption and Abandonment of Organic Farming: An Empirical Investigation of the Irish Drystock Sector. *Journal of Agricultural Economics*, *61*(3), 697–714. https://doi.org/10.1111/j.1477-9552.2010.00260.x

Li, J., Zuo, J., Cai, H., & Zillante, G. (2018) Construction waste reduction behavior of contractor employees: An extended theory of planned behavior model approach. *Journal of Cleaner Production*, *172*, 1399–1408. https://doi.org/10.1016/j.jclepro.2017.10.138

Lindblom, J., Lundström, C., Ljung, M., & Jonsson, A. (2017) Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precision Agriculture*, *18*(3), 309–331. https://doi.org/10.1007/s11119-016-9491-4

Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., & Blackmore, S. (2020) Economics of robots and automation in field crop production. *Precision Agriculture*, *21*(2), 278–299. https://doi.org/10.1007/s11119-019-09667-5

Michels, M., Bonke, V., & Musshoff, O. (2020) Understanding the adoption of smartphone apps in crop protection. *Precision Agriculture*, *21*(6), 1209–1226. https://doi.org/10.1007/s11119-020-09715-5

Michels, M., Fecke, W., Feil, J.-H., Musshoff, O., Pigisch, J., & Krone, S. (2020) Smartphone adoption and use in agriculture: empirical evidence from Germany. *Precision Agriculture*, *21*(2), 403–425. https://doi.org/10.1007/s11119-019-09675-5

Miller, N. J., Griffin, T. W., Ciampitti, I. A., & Sharda, A. (2019) Farm adoption of embodied knowledge and information intensive precision agriculture technology bundles. *Precision Agriculture*, *20*(2), 348–361. https://doi.org/10.1007/s11119-018-9611-4

Mohr, S., & Kühl, R. (2021) Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, *22*, 1816–1844. https://doi.org/10.1007/s11119-021-09814-x

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., Palma, A. de, Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., . . . Purvis, A. (2015) Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. https://doi.org/10.1038/nature14324

Oca Munguia, O. M., & Llewellyn, R. (2020) The Adopters versus the Technology: Which Matters More when Predicting or Explaining Adoption? *Applied Economic Perspectives and Policy*, *42*(1), 80–91. https://doi.org/10.1002/aepp.13007

Pathak, H. S., Brown, P., & Best, T. (2019) A systematic literature review of the factors affecting the precision agriculture adoption process. *Precision Agriculture*, *20*(6), 1292–1316. https://doi.org/10.1007/s11119-019-09653-x
Paustian, M., & Theuvsen, L. (2017) Adoption of precision agriculture technologies by German crop farmers. *Precision Agriculture*, *18*(5), 701–716. https://doi.org/10.1007/s11119-016-9482-5
Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013) Drivers of Precision Agriculture Technologies Adoption: A Literature Review. *Procedia Technology*, *8*, 61–69. https://doi.org/10.1016/j.protcy.2013.11.010
Pretty, J., Benton, T. G., Bharucha, Z. P., Dicks, L. V., Flora, C. B., Godfray, H. C. J., Goulson, D., Hartley, S., Lampkin, N., Morris, C., Pierzynski, G., Prasad, P. V. V., Reganold, J., Rockström, J., Smith, P., Thorne, P., & Wratten, S. (2018) Global assessment of agricultural system redesign for sustainable intensification. *Nature Sustainability*, *1*(8), 441–446. https://doi.org/10.1038/s41893-018-0114-0
Reichardt, M., & Jürgens, C. (2009) Adoption and future perspective of precision farming in Germany: results of several surveys among different agricultural target groups. *Precision Agriculture*, *10*(1), 73–94. https://doi.org/10.1007/s11119-008-9101-1
Reichardt, M., Jürgens, C., Klöble, U., Hüter, J., & Moser, K. (2009) Dissemination of precision farming in Germany: acceptance, adoption, obstacles, knowledge transfer and training activities. *Precision Agriculture*, *10*(6), 525–545. https://doi.org/10.1007/s11119-009-9112-6
Rezaei, R., Safa, L., Damalas, C. A., & Ganjkhanloo, M. M. (2019) Drivers of farmers' intention to use integrated pest management: Integrating theory of planned behavior and norm activation model. *Journal of Environmental Management*, *236*, 328–339. https://doi.org/10.1016/j.jenvman.2019.01.097
Rogers, E. M. (1983) *Diffusion of Innovations* (3rd ed.). New York: The Free Press.
Rübcke von Veltheim, F., & Heise, H. (2021) German Farmers’ Attitudes on Adopting Autonomous Field Robots: An Empirical Survey. *Agriculture*, *11*(3), 216. https://doi.org/10.3390/agriculture11030216
Schwartz, S. H. (1977) Normative Influences on Altruism, *10*, 221–279. https://doi.org/10.1016/S0065-2601(08)60358-5
Sniehotta, F. F., Presseau, J., & Araújo-Soares, V. (2014) Time to retire the theory of planned behaviour. *Health Psychology Review*, *8*(1), 1–7. https://doi.org/10.1080/17437199.2013.869710
Sok, J., Borges, J. R., Schmidt, P., & Ajzen, I. (2021) Farmer Behaviour as Reasoned Action: A Critical Review of Research with the Theory of Planned Behaviour. *Journal of Agricultural Economics*, *72*(2), 388–412. https://doi.org/10.1111/1477-9552.12408
Soper, D. S. (2023). *A-priori Sample Size Calculator for Structural Equation Models* [Computer software]. https://www.danielsoper.com/statcalc
Sparrow, R., & Howard, M. (2021) Robots in agriculture: prospects, impacts, ethics, and policy. *Precision Agriculture*, *22*(3), 818–833. https://doi.org/10.1007/s11119-020-09757-9
Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B. L., Lassaletta, L., Vries, W. de, Vermeulen, S. J., Herrero, M., Carlson, K. M., Jonell, M., Troell, M., DeClerck, F., Gordon, L. J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., . . . Willett, W. (2018) Options for keeping the food system within environmental limits. *Nature*, *562*(7728), 519–525. https://doi.org/10.1038/s41586-018-0594-0
Tamirat, T. W., Pedersen, S. M., & Lind, K. M. (2017) Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agriculturae Scandinavica, Section B — Soil & Plant Science*, *68*(4), 349–357. https://doi.org/10.1080/09064710.2017.1402949
Tey, Y. S., & Brindal, M. (2012) Factors influencing the adoption of precision agricultural technologies: a review for policy implications. *Precision Agriculture*, *13*(6), 713–730. https://doi.org/10.1007/s11119-012-9273-6

Thogersen, J., & Olander, F. (2006) The Dynamic Interaction of Personal Norms and Environment-Friendly Buying Behavior: A Panel Study1. *Journal of Applied Social Psychology*, *36*(7), 1758–1780. https://doi.org/10.1111/j.0021-9029.2006.00080.x

Thomas, F., Midler, E., Lefebvre, M., & Engel, S. (2019) Greening the common agricultural policy: a behavioural perspective and lab-in-the-field experiment in Germany. *European Review of Agricultural Economics*, *46*(3), 367–392. https://doi.org/10.1093/erae/jbz014

Toma, L., Barnes, A. P., Sutherland, L.-A., Thomson, S., Burnett, F., & Mathews, K. (2018) Impact of information transfer on farmers' uptake of innovative crop technologies: a structural equation model applied to survey data. *The Journal of Technology Transfer*, *43*(4), 864–881. https://doi.org/10.1007/s10961-016-9520-5

Toma, L., & Mathijs, E. (2007) Environmental risk perception, environmental concern and propensity to participate in organic farming programmes. *Journal of Environmental Management*, *83*(2), 145–157. https://doi.org/10.1016/j.jenvman.2006.02.004

von Braun, J., Afsana, K., Fresco, L. O., & Hassan, M. (2021) Food systems: seven priorities to end hunger and protect the planet. *Nature*, *597*.

Walter, A., Finger, R., Huber, R., & Buchmann, N. (2017) Opinion: Smart farming is key to developing sustainable agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(24), 6148–6150. https://doi.org/10.1073/pnas.1707462114

Wang, S., Fan, J., Zhao, D., Yang, S., & Fu, Y. (2016) Predicting consumers' intention to adopt hybrid electric vehicles: using an extended version of the theory of planned behavior model. *Transportation*, *43*(1), 123–143. https://doi.org/10.1007/s11116-014-9567-9

Wang, S., Wang, J., Yang, S., Li, J., & Zhou, K. (2020) From intention to behavior: Comprehending residents' waste sorting intention and behavior formation process. *Waste Management (New York, N.Y.)*, *113*, 41–50. https://doi.org/10.1016/j.wasman.2020.05.031

Weersink, A., Fraser, E., Pannell, D., Duncan, E., & Rotz, S. (2018) Opportunities and Challenges for Big Data in Agricultural and Environmental Analysis. *Annual Review of Resource Economics*, *10*(1), 19–37. https://doi.org/10.1146/annurev-resource-100516-053654

Westerink, J., Jongeneel, R., Polman, N., Prager, K., Franks, J., Dupraz, P., & Mettepenningen, E. (2017) Collaborative governance arrangements to deliver spatially coordinated agri-environmental management. *Land Use Policy*, *69*, 176–192. https://doi.org/10.1016/j.landusepol.2017.09.002

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017) Big Data in Smart Farming – A review. *Agricultural Systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023