A Trans-Theoretical Model for Farmers' perceived Usefulness of Digital Risk Management Tools – A Case Study from Germany

Julia B. Block
Georg-August-Universität Göttingen

Marius Michels
Humboldt-Universität zu Berlin

Oliver Mußhoff
Georg-August-Universität Göttingen

Abstract

Digital risk management tools (RMTs) are promising to help farmers manage risk. However, these recently developed tools are still unexplored and hardly used by farmers. This study is the first to investigate how German farmers perceive the usefulness of digital RMTs and which factors influence them. A novel modification of the trans-theoretical model was made to determine farmers' perceived usefulness gradually. The regression results show that, on average, farmers perceive digital RMTs as potentially useful. Perceptions are positively influenced by a higher level of education, full-time employment on the farm, use of mobile devices and a higher perceived importance of digital tools. The study contributes to the literature by investigating the extent to which farmers are willing to accept the combination of digitisation and risk management. The results are of interest to policy makers involved in digital agriculture and to agricultural tool providers, as they offer first insights into farmers' acceptance of digital RMTs. Researchers benefit from the successfully applied trans-theoretical model fitting.

Keywords

digital risk management tools; digitisation, German farmers; risk management; trans-theoretical model

1 Introduction

Digital risk management tools (RMTs)[1] have been developed to help farmers manage risks. In view of the globalisation of trade in commodities, changing consumer behaviour, and extreme weather situations caused by climate change, risk management has become more important on individual farms (GÖMANN et al., 2015; LUNT et al., 2016; GRILLAKIS, 2019; HARKNESS et al., 2020). Digital RMTs help to uncover hidden risks in everyday life. Step by step, farmers select framework conditions and sources of risk from an extensive catalogue, make individual entries and link the influencing factors. As a result, farmers receive an individual digital risk checklist for everyday situations or special projects, e.g. expansion of pig fattening. This can also be informative for banks and consultants (WAPPNET, 2020).

In an increasingly digitalised world, the adoption of digital tools is crucial for risk management in agriculture, provided that they are useful and facilitate farmers' work. There are few digital RMTs, but despite the potential benefits, they are hardly used. There is no research yet on the use of digital RMTs by farmers. The decision on adoption depends largely on first impressions. As a first step, it is worthwhile to investigate the extent to which farmers find digital RMTs useful. Perceived usefulness allows conclusions to be drawn about the adoption decision. Several studies agreed that higher perceived usefulness of new technologies increases the willingness to adopt them (TEY and BRINDAL, 2012; ROSE et al., 2016; ZHENG et al., 2019).

The aim of the study is to analyse farmers' perceived usefulness of digital RMTs. More specifically, we want to explore the extent to which farmers find digital RMTs useful and how personal as well as farm characteristics influence farmers' perceptions. We contribute to the literature by gaining initial insights

[1] In the following, we distinguish between risk management tools (RMTs) and risk management instruments (RMIs). By RMIs we mean risk mitigation strategies, e.g. diversification or hail insurance. In this context, (digital) RMTs help to get an overview of possible risk factors and can support the decision for or against an RMI.

DOI: 10.30430/ gjae.2023.0330

into farmers' willingness to accept digital RMTs. As digital RMTs combine digitisation and risk management, they could potentially represent a kind of intermediate step towards artificial intelligence (AI) in the field of risk management. Our study therefore allows us to make initial assumptions about farmers' readiness for AI in risk management.

To achieve the objectives of the study, an online survey was conducted with 160 German farmers in 2020, which included a trans-theoretical model of perceived usefulness (TTMU). By modifying PROCHASKA and VELICER'S (1997) trans-theoretical model of behavioural change (TTMC) into a TTMU, we were able to assess farmers' perceived usefulness gradually, at a given point in time. The TTMU offers deeper insights into farmers' actual perceptions than binary classifications, even though it is less commonly used. In the TTMU, farmers are classified into chronological and sequential stages, depending on how they currently perceive the benefits of digital RMTs. We applied an ordered logit model to investigate the factors that influence farmers' perceived usefulness of digital RMTs and thus the transition to another stage within the TTMU. We focused on German farmers because Germany has a diverse production and faces many different climatic challenges due to the different biogeographical regions (EUROPEAN PARLIAMENT, 2018). Furthermore, this study is well placed considering that Germany is aiming to expand its pioneering role in digitisation in agriculture (EUROPEAN PARLIAMENT, 2018; BMEL, 2021).

As we shed light for the first time on the usefulness of digital RMTs as currently perceived by farmers, our findings are of particular interest to policy makers and researchers working on digitisation and/or risk management in agriculture, as well as to tool providers. We uncover farmers' readiness for digital RMTs as precursors to AI in risk management and identify pioneer users. Policy makers and tool developers will give advice on how to efficiently support farmers in digitising their risk management and how to reach more farmers. Through a novel adaptation of the trans-theoretical model (TTM), we investigate whether this construct is applicable in the context of digitisation and risk management in agriculture. Researchers benefit from this adaptation as it expands the possibilities for applying the TTM.

The remainder of this study is structured as follows: Section 2 derives factors that might influence farmers' perceived usefulness of digital RMTs, considering the literature on digitisation and risk management. The design of the TTMU, econometric modelling and data collection are presented in Section 3. Section 4 discusses the results, followed by the conclusions and perspectives for further research in Section 5.

2 Potential Influential Factors derived from Literature on Digitisation and Risk Management

In our explorative study, we dedicate ourselves to a new market for which we combine two already known research areas: digitisation and risk management in agriculture. Digital RMTs, the combination of both topics, are relatively new and largely unknown even among farmers, which may be justified given the lack of literature. In what follows, we refer to the literature that identifies factors influencing the adoption of digitisation and risk management in agriculture. From this, we derive what influence these factors might have on the perceived usefulness and thus on the acceptance of digital RMTs.

Older farmers are reluctant to use a digital tool, but are more interested in protecting themselves from risks: Older farmers are less likely to adopt technologies such as precision agricultural technologies (PATs) (PAUSTIAN and THEUVSEN, 2017; TAMIRAT et al., 2018) and smartphones (MICHELS et al., 2019) than younger farmers. BARNES et al. (2019) argue that a shorter planning horizon of older farmers is a barrier to investment in PATs. ROBERTS et al. (2004) explain that older farmers are less willing to change their habits, which according to ROSE et al. (2016) is a major barrier to the adoption of new technologies. In terms of risk attitudes, age has been found to have a negative effect on risk taking (VROOM and PAHL, 1971; DOHMEN et al., 2011) and a positive effect on risk perception (OTANI et al., 1992; COHN et al., 1995). This suggests that older people are more risk averse and perceive the same risks as greater in magnitude than younger people. ADNAN et al. (2020) found mixed results on the impact of age on farmers' adoption of risk management instruments (RMIs), e.g. age is positively correlated with adoption of contract farming but negatively correlated with diversification. No clear expectation can be derived from the combination of both literature areas. Since the prerequisite for using a digital RMT is to practice risk management, we expect that older farmers will find a digital RMT more useful.

The educational level of farmers has a positive influence on the adoption of technologies and some RMIs: Farmers with higher levels of education are more likely to adopt PATs than farmers with lower levels of education (TEY and BRINDAL, 2012; AUBERT et al., 2012; PIERPAOLI et al., 2013). It is assumed that farmers with higher education have better technological and analytical skills (KOTSIRI et al., 2011; PAUSTIAN and THEUVSEN, 2017) and a better understanding of the application of new technologies (AUBERT et al., 2012). The effect of education on risk attitudes varies. BAR-SHIRA et al. (1997) and HARRISON et al. (2007) found that higher education leads to more risk-averse attitudes, while MOSCARDI and JANVRY (1977) and HARTOG et al. (2002) found the opposite. ADNAN et al. (2020) investigated a positive correlation between farmers' education level and the use of some RMIs, e.g. contract farming, diversification, and precautionary savings. Based on this and the above studies on the acceptance of new technologies, we expect that higher levels of education will positively influence farmers' perceived usefulness of digital RMTs.

Full-time farmers (who do not earn off-farm income) are more likely to adopt new technologies and RMTs: Farmers who work full-time on their farm have a greater interest in using new technologies and are more willing to adopt PATs (DABERKOW and MCBRIDE, 2003; KOTSIRI et al., 2011). Part-time farmers have off-farm income, which according to VELANDIA et al. (2009) is a form of diversification and allows farmers to take more risk, thus reducing incentives to introduce RMTs. They also found that (higher) off-farm income reduces the likelihood of using one of the three RMTs considered (crop insurance, forward contracting, spreading sales) or all three at the same time. Combining both literature areas, we derive the expectation that full-time farming will have a positive impact on farmers' perceived usefulness of digital RMTs.

Farmers with larger farms are more willing to adopt new technologies, but show less interest in risk management: TEY and BRINDAL (2012) and PAUSTIAN and THEUVSEN (2017) found that farmers with larger farms are more likely to use PATs. DABERKOW and MCBRIDE (2003) and MICHELS et al. (2020) found that as farm size increases, the likelihood of using drones increases. The positive impact of farm size on technology adoption is expected mainly due to economies of scale (PAUSTIAN and THEUVSEN, 2017). Due to economies of scale and better management capacities, larger farms are also better able to take risks and offset shocks (DOHMEN et al., 2011; EL BENNI et al., 2016; ADNAN et al., 2020), which reduces the need for risk management. VELANDIA et al. (2009) pointed out that the relationship between farm size and the adoption of different RMTs seems to be ambiguous and depends on the specific instrument. The combination of both literature backgrounds does not allow for a clear expectation. However, we expect that farmers with larger farms are more willing to adopt a new digital tool for risk monitoring and therefore find digital RMTs more useful.

Soil quality has a positive impact on technology adoption, but is less well studied in terms of risk management: Farmers whose farm has better soil quality are more willing to use PATs (DABERKOW and MCBRIDE, 2003; TEY and BRINDAL, 2012). TIEDEMANN et al. (2011) found that different soil, climate and relief conditions can lead to different risk attitudes among farmers. Ignoring such circumstances would lead to underestimating the efficiency of farms with unfavourable environmental conditions and distort farmers' risk management. An empirical study about farmers' risk management in the north-east of Germany shows that different soil requirements force caution to varying degrees and lead to different ways of dealing with upcoming risks (SCHAPER et al., 2012). Although the literature on PATs suggests a positive effect of soil quality on the adoption of digital tools, we believe that farmers with poorer soil quality are more likely to be interested in a digital risk monitoring tool due to lower yields and a lower safety buffer. Therefore, we expect that farmers with poorer soil quality will find digital RMTs more useful.

Farmers with a higher proportion of their own land are more willing to adopt new technologies, especially PATs, but less willing to adopt RMIs: Farmers can manage their own land more favourably than rented land and enjoy even more benefits from their farm management, leading to higher uptake of new technologies (ROBERTS et al., 2004; TEY and BRINDAL, 2012). At the same time, a higher share of own land increases the ability to bear risks, as there are fewer payment obligations and more flexibility, which reduces risk aversion and the need for RMIs (VELANDIA et al., 2009; VIGANI and KATHAGE, 2019). VELANDIA et al. (2009) found that farmers with a higher proportion of their own land tend not to use RMIs such as crop insurance or forward contracts. The contrasting impacts of land tenure on technology adoption and risk management do not allow for clearcut expectations. Nevertheless, we expect that farmers with a higher proportion of their own land find digital RMTs less useful. In other words, a higher proportion of rented land will have a positive impact on farmers' perceived usefulness of digital RMTs.

Previous experience with digitisation has a positive effect on farmers' adoption of technologies and on some RMIs: Adoption of PATs is more likely if farmers are already using similar technologies (ISGIN et al., 2008; GRIFFIN et al., 2017) or computers (DABERKOW and MCBRIDE, 2003; KOTSIRI et al., 2011; D'ANTONI et al., 2012). Farmers who use computers are also more likely to participate in hedging and futures markets (MISHRA and EL-OSTA, 2002), which are RMIs. As digital RMTs require a computer, smartphone or tablet, we expect that farmers who already use mobile devices will find digital RMTs more useful.

The perceived importance of digital tools has a positive impact on technology adoption: Farmers who expected PATs to be profitable in the future and important in five years used PATs earlier than others (WATCHARAANANTAPONG et al., 2014). ROSE et al. (2016) pointed out that perceived relevance (and ease of use) is one of the most influential reasons whether a particular decision support tool is used. We expect that the perceived usefulness of digital RMTs will be positively influenced by the perceived importance of digital support tools over the next 10 years.

3 Material and Methods

3.1 Trans-Theoretical Model of Perceived Usefulness

The TTM generally consists of five core constructs: stages of change, processes of change, decisional balance, self-efficiacy and temptation. In the following, we mainly refer to the first two constructs.

The stages of change represent a temporal dimension and illustrate that behaviour change is a process, i.e. a progression through gradual stages (PROCHASKA and VELICER, 1997). In the first stage, 'Pre-Contemplation', people are not destined to change their behaviour. They usually avoid getting information or talking about the issue. In the second stage, 'Contemplation', people have the basic intention to change. They are aware of the advantages of change, but also of the disadvantages, which is why they stay in this stage for a long time. In the third stage, 'Preparation', people are supposed to take action in the near future by having a concrete plan for change. In the 'Action' stage, people change their behaviour (PROCHASKA and VELICER, 1997).

Processes of change are like independent variables that explain a person's transition from one stage to another. PROCHASKA and VELICER (1997) described ten processes with considerable influence. In this study, we refer to personal and farm characteristics that can influence stage affiliation and progression (see Section 2).

The other three constructs of the TTM relate to the perceptions, confidence and habits of the individual, but are not considered further in this study. Decisional balance reflects the person's perceived advantages and disadvantages of a change. Self-efficacy describes people's confidence to cope with risky situations without falling back a stage. Temptation is the urge to perform a certain habit in a difficult situation.

The application of the TTM in an agricultural context is rare. The TTM was originally developed to analyse behavioural change (= TTMC), especially deep-rooted health behaviours, e.g. decisions regarding smoking behaviour or physical activity of prediseased people (PROCHASKA and VELICER, 1997; KIRK et al., 2010). Nevertheless, some studies have modified the TTMC to analyse farmers' adoption. LEMKEN et al. (2017) analysed the adoption of intercropping by farmers. MICHELS et al. (2020) analysed the adoption of drones by farmers. Both applied the TTM to determine adoption trends by reformulating the statements of the stages. MICHELS et al. (2020) then called it the trans-theoretical model of adoption (TTMA).

Following LEMKEN et al. (2017) and MICHELS et al. (2020), we took the TTMC and modified it in a TTMU to answer our research questions. Compared to LEMKEN et al. (2017) and MICHELS et al. (2020), we took a step back and asked about perceived usefulness rather than adoption. We did this because there are very few digital RMTs so far (which are still relatively unknown even among farmers) and therefore we had to work with a fictious digital RMT. Thus, we did not adopt the TTMA, but modified the TTMC statements for each stage according to perceived usefulness (as LEMKEN et al. (2017) and MICHELS et al. (2020) did according to adoption) and called it TTMU (see Table 1). Farmers select a statement (referring to a stage) that is best suited to describe their current perception of usefulness. In this way, we can gradually assess farmers' perceived usefulness of digital RMTs.

Table 1. Trans-theoretical model of perceived usefulness (TTMU) for digital RMTs

Stage	TTMC Concept	TTMU Modification[a)]	Coding
Pre-Contemplation	No intention or motivation to change	The use of a digital RMT is currently of no benefit for me.	1
Contemplation	Intention to change	The use of a digital RMT could currently be useful for me.	2
Preparation	Intention to change with a concrete plan	The use of a digital RMT could currently be of great benefit to me.	3
Action	Behaviour has changed	The use of a digital RMT is certainly of great benefit to me at the moment.	4

[a)] Translated from German into English.
Source: Illustration based on PROCHASKA and VELICER (1997) and adapted by LEMKEN et al. (2017) and MICHELS et al. (2020).

In relation to the first two TTM constructs, the TTMU helps answer the question of which stage of change farmers are in with regards to the adoption of digital RMTs, and which processes of change affect farmers as they move from one stage to the other. Due to the few existing digital RMTs and the small number of farmers using digital RMTs so far, we expect that many farmers are in the Pre-Contemplation or Contemplation stage. With targeted intervention strategies, they could enter the Action stage.

3.2 Econometric Model

To identify the factors that influence farmers' perceived usefulness and thus the TTMU stage they are in, we ran an ordered logit model. The dependent variable (= TTMU) represented by $y*$ in Equation (1) is ordinal with four categories. Hence, we used an ordered logit model to estimate the influence of the independent variables presented in Section 2 on the dependent variable (VERBEEK, 2008):

$$x^* = x\beta + e \tag{1}$$

where vector X represents the independent variables derived in Section 2 and vector β contains the regression coefficients. A distribution function with an expected value of zero is assumed for the error term e. To analyse the relationship between the variables, the independent variables represent the crossing of the threshold value of the dependent variable $y*$, which can be interpreted as gradual usefulness stages:

$$y = \begin{cases} 0 \; if \; y^* \leq \mu_1, \\ 1 \; if \; \mu_1 < y^* \leq \mu_2, \\ 2 \; if \; \mu_2 < y^* \leq \mu_3, \\ \quad . \\ \quad . \\ \quad . \\ J \; if \mu_j < y^* \end{cases} \tag{2}$$

where μ_j represents the ordered thresholds, i.e. the endpoints of each observable stage, and J indicates the number of graded usefulness stages (VERBEEK, 2008).

Based on Equation (1), we set up the following equation to investigate the influence of personal and farm characteristics on the assignment of farmers to a TTMU stage:

$$\begin{aligned} TTMU_i = \beta_0 &+ \beta_1 Age \\ &+ \beta_2 Education \\ &+ \beta_3 Full\_Time \\ &+ \beta_4 Farm\_Size \\ &+ \beta_5 Soil\_Quality \\ &+ \beta_6 Rented\_Land \\ &+ \beta_7 Mobile\_Devices \\ &+ \beta_8 Importance\_Future \\ &+ e_i \end{aligned} \tag{3}$$

where i is the individual respondent and e_i is the error term with a logistic distribution. The empirical analysis is carried out with the software 'STATA 17' and the command *ologit*.

To ensure the robustness of the results in advance, multicollinearity must be eliminated. To test for multicollinearity, the calculated variance inflation factors (VIFs) must be below 5 and the tolerances above 0.1 (CURTO and PINTO, 2011). We determined VIFs between 1.07 and 1.27 (mean VIF = 1.16) and tolerances between 0.79 and 0.94 (mean tolerance = 0.86), indicating that multicollinearity does not affect the robustness of our results.

Another robustness check is the verification of the assumption of a parallel regression. A Brant test was carried out for this (GUZMAN-CASTILLO et al., 2015). Initially, the assumption was violated. Since only one farmer was classified in stage 4 (Action stage), we merged stage 3 and stage 4 of the TTMU.

Because we expect that the majority of farmers belong to the Pre-Contemplation or Contemplation stage, merging the Preparation and Action stage will not have a major impact on content. Here, we also follow LEMKEN et al. (2017), who also merged two stages, which removes the violation of the assumption. This procedure avoids switching to an alternative model that cannot equally account for the ordinal scaled dependent variable. Subsequently, a statistically non-significant Brant test ($\chi^2 = 3.18$ $p = 0.92$) showed that the parallel regression assumption is not compromised, i.e. that all coefficients are the same for all stages of the dependent variable. So only one set of coefficients needs to be calculated.

3.3 Data Collection and Survey Design

Primary data collected in an online survey of 160 German farm managers between May and June of 2020 were used for the analysis. The survey was sent to farmers by e-mail. The e-mail addresses were collected in previous surveys where farmers had explicitly expressed their interest in being invited by us to participate in further surveys. At least 251 farmers participated in the online survey. After removing incomplete questionnaires, 160 fully answered questionnaires were included in the analysis. Our sample size of 160 farmers has a margin of error of 7.75% at a confidence level of 95%, based on the German farmer population of 262,776 farms in 2020 (BARTLETT et al., 2001). The mean completion time of the survey was 19 minutes.

The survey contains questions on general information and on the fictious digital RMT. First, farmers were asked to provide information on personal and farm characteristics, current risk management and the use of mobile devices. In the second part of the questionnaire, we presented a fictitious digital RMT to the farmers (see Appendix A). We designed it based on the existing digital RMT 'Wappnet Agrar' (WAPPNET, 2020). Farmers than had to rate statements about the tool to identify their requirements, but this is not discussed further in this study. Finally, we asked farmers to answer the adapted TTMU question from their actual perspective (see Appendix B).

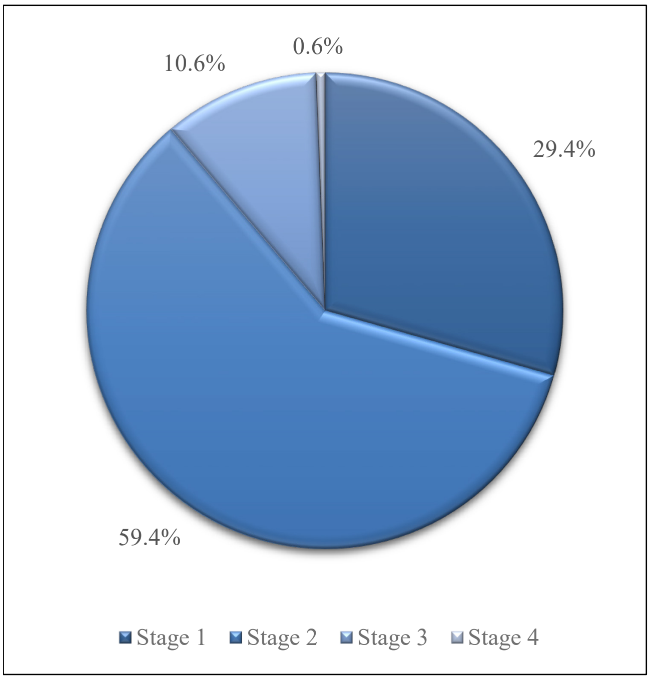
4 Results and Discussion

4.1 Descriptive Results

The average farmer in our sample is in the Contemplation stage (average value = 1.82), i.e. they are aware of possible advantages/disadvantages of digital RMTs but do not yet have concrete plans to use them (PROCHASKA and VELICER, 1997). Figure 1 shows the distribution of farmers across the four stages of the TTMU. Among the surveyed farmers, 29% indicated that the use of digital RMTs is of no benefit to them at present, and they are therefore classified as stage 1 (Pre-Contemplation stage). The vast majority, 59% of the farmers, stated that the use of digital RMTs could be useful for them at this time, which is indicative of stage 2 (Contemplation stage). For 11%, the use of digital RMTs could be of great benefit at the moment, which corresponds to stage 3 (Preparation stage). Only one farmer in our sample (0.6%) feels that the use of digital RMTs is certainly of great benefit to him or her at this time and is classified as stage 4 (Action stage).

Our sample differs from the German farmer population mainly in terms of farm size and educational level, which does not suggest representative results. Table 2 shows the descriptive statistics for each independent variable presented in Section 2 and Equation (3) (Section 3.2). The sample is close to the average German farmer in terms of age ([our sample:] 46 years vs. [German average:] 53 years), share of

Figure 1. Distribution of consulted farmers among the four stages of the TTMU in % (N = 160)[a)]



a) Stage 1 = The use of a digital RMT is currently of no benefit to me. Stage 2 = The use of a digital RMT could currently be useful for me. Stage 3 = The use of a digital RMT could currently be of great benefit to me. Stage 4 = The use of a digital RMT is certainly of great benefit to me at the moment.
Source: Own data and calculations.

Table 2. Descriptive statistics (N = 160)

Variable	Description	Mean/Share	S.D.	Min	Max	German Average[a)]
Age	Famers age in years	45.52	12.45	21.00	74.00	53.00
	≤25 years	0.03	-	0.00	1.00	0.01
	>25 and ≤35	0.24	-	0.00	1.00	0.07
	>35 and ≤45	0.25	-	0.00	1.00	0.17
	>45 and ≤55	0.21	-	0.00	1.00	0.29
	>55 years	0.27	-	0.00	1.00	0.47
Education	1, if the farmer holds a university degree; 0 otherwise	0.48	-	0.00	1.00	0.09
Full_Time	1, if the farmer is full-time farmer; 0 otherwise	0.48	-	0.00	1.00	0.58
Farm_Size	Farm size in hectares (arable land + pasture land)	259.76	390.16	5.00	2550.00	63.00
	≥5 and ≤10 hectares	0.01	-	0.00	1	0.17
	>10 and ≤20 hectares	0.02	-	0.00	1	0.20
	>20 and ≤50 hectares	0.09	-	0.00	1	0.23
	>50 and ≤100 hectares	0.26	-	0.00	1	0.17
	>100 and ≤200 hectares	0.27	-	0.00	1	0.10
	>200 and ≤500 hectares	0.25	-	0.00	1	0.04
	>500 hectares	0.11	-	0.00	1	0.02
Soil_Quality	Soil quality in soil points	49.84	18.66	10.00	90.00	n.a.
Rented_Land	Share of rental land in percent	50.78	26.88	0.00	100.00	66.37
Mobile_Devices	1, if the farmer uses smartphone and tablet for farming purposes; 0 otherwise	0.43	-	0.00	1.00	n.a.
Importance_Future[b)]	\`How important will adapting to digital farming and using digital support tools be to you within the next 10 years, in terms of your farms profitability?\`[c)]	3.91	1.02	1.00	5.00	n.a.

S.D. = Standard deviation; n.a. = not available
[a)] German Average from the farmer population (FEDERAL STATISTICAL OFFICE OF GERMANY, 2019).
[b)] 5-point Likert-scale (1 = not important; 5 = very important)
[c)] Translated from German into English.
Source: Own data and calculations; FEDERAL STATISTICAL OFFICE OF GERMANY (2019).

full-time farmers (48% vs. 58%) and share of rented land (51% vs. 66%) (FEDERAL STATISTICAL OFFICE OF GERMANY, 2019). The age difference is mainly due to the fact that farmers up to 35 years of age are overrepresented in our study, while farmers over 55 years of age are underrepresented compared to the German average. There are larger differences in farm size ([our sample:] 260 ha vs. [German average:] 63 ha) and educational level (48% with a university degree vs. 9% with a university degree). More precisely, a farm size up to 50 ha is underrepresented in our sample, while a farm size above 100 ha is overrepresented compared to the German average. Our sample is not representative of the current agricultural population in Germany, so the results of this study can only be interpreted within the sample.

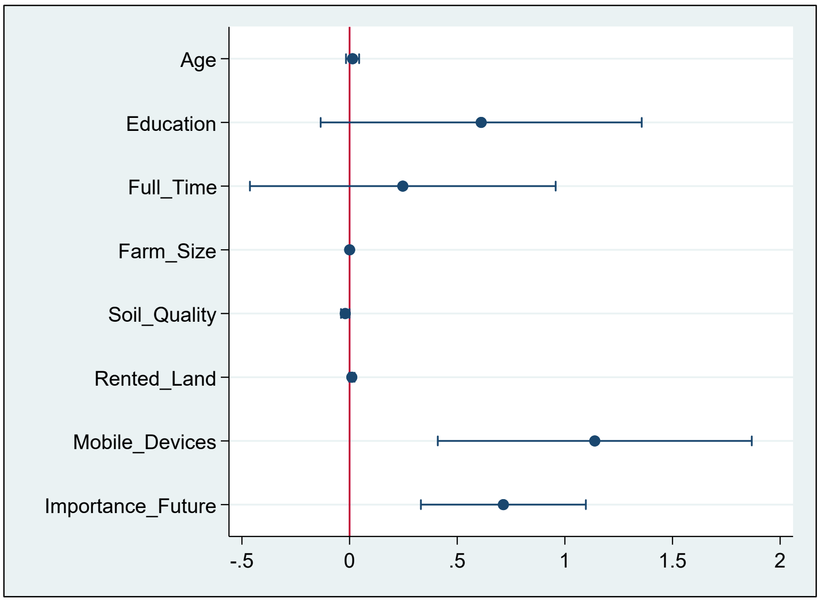
About half of the farmers in our sample use mobile devices on their farms. Specifically, smartphones and tablets are used by 43% of respondents for agricultural purposes. On average, the surveyed farmers rate digital support tools as rather important (3.91 points on a 5-point Likert-scale[2]) for farm profitability over the next 10 years (see Appendix C).

4.2 Regression Results

The results of the ordinal logistic regression show the extent to which the independent variables influence farmers in terms of their TTMU stage and thus the perceived usefulness of digital RMTs. The regression results are presented in Figure 2 by graphing the

2 Respondents often view responses (often five) to a Likert-item as points on a continuum from low to high, with response distributions resembling those on a scale line with equal spacing between points (WILLITS et al., 2016). Many researchers choose to treat ordinal scales as interval scales, which allows the calculation of means and standard deviations. According to STEVENS (1946), LORD (1953) and KNAPP (1990), this can lead to many fruitful and meaningful results. On this basis, we use means and standard deviations in Table 2.

Figure 2. Coefficients and 95% confidence intervals of factors in an ordered logit model that may influence farmers' perceived usefulness of digital RMTs (N = 160)[a)]



[a)] Points represent coefficients; horizontal lines represent confidence intervals. The vertical line represents the reference line at zero, the crossing of which indicates statistical non-significance.
Source: Own illustration calculated and presented with STATA 17 and based on own data.

coefficients and their confidence intervals in coefficient plots. A coefficient plot is a useful visualisation of regression results in showing the effects in the model with lines indicating the width of the 95% confidence intervals. Variables whose lines (confidence intervals) intersect the reference line at zero are not statistically significant. For completeness, we added a table with the coefficients, the associated standard errors, and the 95%-confidence intervals in Appendix D. The calculation of the predicted probabilities (see Appendix E) shows that the average farmer in the sample has a probability of 68% of being classified in the Contemplation stage (TTMU = 2). This is roughly in line with our descriptive results, according to which about 60% of the farmers in our sample belong to the Contemplation stage.

As shown in Figure 2, age has a slightly positive but almost neutral influence on farmers' perceived usefulness of digital RMTs. We expected a positive effect, as older farmers tend to be more risk averse (Vroom and Pahl, 1971; Dohmen et al., 2011), suggesting a higher interest in risk management. However, older farmers are also less likely to adopt new technologies (Paustian and Theuvsen, 2017; Tamirat et al., 2018), suggesting a negative influence of age on the adoption of digital tools. The contrasting effects of age on adoption of new technologies and risk management described in the literature may explain why age does not have a considerable impact on farmers' transition from one usefulness stage to the next in terms of digital RMTs.

Education has a positive influence on farmers' perceived usefulness of digital RMTs, suggesting that farmers with higher level of education are assigned to a higher TTMU stage. We also expected a positive effect, which is in line with several studies on the acceptance of technologies and RMIs. Literature suggests that famers with higher levels of education are more likely to adopt PATs (Tey and Brindal, 2012; Aubert et al., 2012; Pierpaoli et al., 2013) and RMIs, e.g. contract farming and diversification (Adnan et al., 2020).

Full-time farming clearly has a positive effect on farmers' perceived usefulness of digital RMTs, suggesting that full-time farmers are more likely to be at a higher TTMU stage. This is consistent with our expectation that full-time farmers find digital RMTs more useful. We derived this from the converging literature on digitisation and risk management, which shows that full-time farmers are more likely to use PATs (Daberkow and McBride, 2003; Kotsiri et al., 2011) and RMTs (Velandia et al., 2009).

Farm size does not seem to have an impact on farmers' perceived usefulness of digital RMTs (see Figure 2). The (almost) neutral effect indicates that farmers with small-to-medium sized farms have the same chances of reaching a higher TTMU stage as farmers managing larger farms. We found opposite results in the literature for the effects of farm size. Farmers with larger farms are more likely to adopt PATs (Tey and Brindal, 2012; Paustian and Theuvsen, 2017), but also have a greater risk capacity, indicating a lower need for risk management (Adnan et al., 2020). These opposing effects could be the reason why farm size has almost no influence on farmers' perception of digital RMTs.

Soil quality has a slightly negative impact on farmers' perceived usefulness of digital RMTs, suggesting that farmers with poorer soil quality are more likely to be at a higher TTMU stage. This is consistent with our expectation that lower soil quality leads to higher perceived usefulness of effective risk monitoring tools such as digital RMTs, as yields are lower and safety buffer is smaller. Conversely, the literature on digitisation says that farmers with better soil qualities are more willing to use PATs (DABERKOW and MCBRIDE, 2003; TEY and BRINDAL, 2012).

Rented land has a slightly positive influence on farmers' perceived usefulness of digital RMTs. We expected that farmers with a higher proportion of rented land would find digital RMTs more useful, as they are less able to bear risk, have a higher risk aversion, and a higher need for RMIs (VELANDIA et al., 2009; VIGANI and KATHAGE, 2019). However, farmers with a higher proportion of rented land are less likely to adopt new technologies and PATs (ROBERTS et al., 2004; TEY and BRINDAL, 2012). As with the factors age and farm size, there are also opposing effects in the literature of the influence of rented land on the adoption of technologies and RMIs. Moreover, as with the factors age and farm size, the effect of rented land on the allocation of farmers to a TTMU stage is almost neutral. It follows that factors which show opposite effects on the adoption of technologies and RMIs in the literature do not have a considerable effect on the adoption of both together (digital RMTs) in our study. This suggests that focusing on only one part of the literature, e.g. only digitisation, is not sufficient to derive initial expectations about factors that influence the combination of digitisation and risk management.

The use of mobile devices has a positive impact on farmers' perceived usefulness of digital RMTs. Note that the use of mobile devices has the greatest influence among the factors studied. Farmers using mobile devices are more likely to be at a higher TTMU stage. We expected this result, as PATs adoption and hedging participation is more likely when farmers are already using similar technologies or computers (MISHRA and EL-OSTA, 2002; D'ANTONI et al., 2012; GRIFFIN et al., 2017).

The perceived importance of digital support tools in the future has a clear positive influence on farmers' perceived usefulness of digital RMTs. Farmers who consider digital tools to be important are more likely to be at a higher TTMU stage, i.e. they consider digital RMTs to be more useful. Since WATCHARAANANTAPONG et al. (2014) found that farmers who believed PATs would be important in five years adopted PATs earlier than others, we expected this result.

5 Conclusions

Digital RMTs help farmers monitor and manage risks. Volatile agricultural markets, climate change and political changes pose new challenges to farmers and make risk management even more complex (GÖMANN et al., 2015; LUNT et al., 2016; GRILLAKIS, 2019). Digital RMTs assist farmers in identifying hidden risks in everyday farming, developing a structured overview of all risks and deciding on appropriate risk management strategies (WAPPNET, 2020). So far, there are only a few digital RMTs, which are hardly used by farmers and are still relatively unexplored in research and in practice.

To gain initial insights into farmers' adoption process, the study aims to analyse farmers' perceived usefulness of digital RMTs gradually at a point in time and the factors influencing adoption. For this purpose, we conducted an online survey with 160 German farmers in spring 2020 and implemented a novel modification of the TTMC called TTMU. The TTMU assigns farmers to different temporal stages according to their perceived usefulness and thus offers deeper insights into farmers' actual perceptions than, for example, binary classifications. We estimated an ordered logit model to identify factors that influence farmers' perceived usefulness and thus the transition from one TTMU stage to the next.

The evaluation of the successfully applied TTMU shows that the average farmer in our sample perceives digital RMTs as potentially useful at this point, which corresponds to the second of four stages (Contemplation stage). This indicates that, on average, farmers are aware of the possible advantages and disadvantages of digital RMTs, but do not yet have concrete plans for their use. Consequently, farmers are on average two steps away from adopting digital RMTs. As digital RMTs can potentially be seen as an intermediate step on the way to using AI in risk management, farmers are probably still much further away from accepting AI than digital tools in risk management.

The results of the ordered logit model show that farmers in our sample who have higher levels of education, work full-time on the farm, use mobile devices for farming purposes and consider digital tools important for the future find digital RMTs more useful. These farmers are more likely to be at a higher TTMU stage. Farmers' age, farm size, soil quality and share of rented land have almost neutral effects on the perceived usefulness of digital RMTs.

In our case, looking at and combining the two literature fields of digitisation and risk management was well suited for deriving factors influencing farmers' perceived usefulness of digital RMTs. If we could derive clear expectations from the literature on digitisation and risk management for one factor, e.g. level of education, this factor indeed shows the presumed effect on the perceived usefulness of digital RMTs. An exception is the factor 'soil quality', for which however, comparatively little literature is available. For age, farm size and share of rented land, we found contrasting effects in the literature regarding their effect on the adoption of new technologies and RMIs and could not derive any clear expectations. Accordingly, they showed almost neutral effects on the perceived usefulness of digital RMTs.

As we contribute to the literature by identifying farmers' readiness for digital RMTs and the factors that influence adoption, our research is of interest to policy makers and researchers working on digitisation and risk management in agriculture, as well as to tool providers. By identifying pioneer users, we provide guidance to policy makers and tool providers on how to develop efficient strategies to encourage farmers to digitise their risk management. Above all, they can improve farmers' access to mobile devices and raise awareness of the importance of digital tools. This can lead to an increase in the perceived usefulness and thus adoption of digital RMTs. Furthermore, our findings provide policy makers with first insights into farmers' readiness to use AI in terms of risk management. It may be of interest to researchers that the literature on digitisation and risk management is suitable for making initial expectations about what influences the adoption of digital RMTs. Additional benefit comes from our successful application of the TTM in the field of digital risk management in agriculture, as it supports the adaptation of a TTM in further research areas.

Subsequent research can focus on a larger sample size, more influencing factors and the influence of the formulation of TTM statements. Our results are subject to reservations, as the sample is not representative of the German agricultural population. For further studies, it is recommended to use a larger sample as well as samples from other countries, e.g. countries with a lower uptake of mobile devices. With regard to the inconsiderable effects of some personal and farm-specific characteristics on the perceived usefulness of digital RMTs, we recommend the use of latent variables for further research to extend our results. In contrast to easily observable characteristics, latent variables give a deeper insight into a person's behaviour, helping to understand farmers' motivational structures, which is important for promoting acceptance (SOK et al., 2021; OWUSU-SEKYERE et al., 2022). Although we provided a detailed introductory text for the fictitious digital RMT, farmers may have had difficulty answering some questions because they lacked a connection to reality. This limits the validity of our results. In order for the TTM to be used without hesitation, future research could investigate whether the wording of the TTM statements has an influence on the response.

References

ADNAN, K.M.M., L. YING, Z. AYOUB, S.A. SARKER, R. MENHAS, F. CHEN and M. YU (2020): Risk Management Strategies to Cope Catastrophic Risks in Agriculture: The Case of Contract Farming, Diversification and Precautionary Savings. In: Agriculture 10 (8): 351.

AUBERT, B.A., A. SCHROEDER and J. GRIMAUDO (2012): IT as enabler of sustainable farming: An empirical analysis of farmers' adoption decision of precision agriculture technology. In: Decision Support Systems 54 (1): 510-520.

BARNES, A.P., I. SOTO, V. EORY, B. BECK, A. BALAFOUTIS, B. SÁNCHEZ, J. VANGEYTE, S. FOUNTAS, T. VAN DER WAL and M. GÓMEZ-BARBERO (2019): Exploring the adoption of precision agricultural technologies: A cross regional study of EU farmers. In: Land Use Policy 80: 163-174.

BAR-SHIRA, Z., R.E. JUST and D. ZILBERMAN (1997): Estimation of farmers' risk attitude: an econometric approach. In: Agricultural Economics 17 (2-3): 211-222.

BARTLETT, J.E., J.W. KOTRLIK and C.C. HIGGINS (2001): Organizational research: Determining appropriate sample size in survey research. Information Technology, Learning, and Performance Journal 19 (1): 43-50.

BMEL (2021): More than 50 million euros for digital trial fields in the agricultural sector. https://www.bmel.de/EN/topics/digitalisation/digital-trial-fields.html, call: 2.5.2022.

COHN, L.D., S. MACFARLANE, C. YANEZ and W.K. IMAI (1995): Risk-perception: differences between adolescents and adults. In: Health Psychology 14 (3): 217-222.

CURTO, J.D. and J.C. PINTO (2011): The corrected VIF (CVIF). In: Journal of Applied Statistics 38 (7): 1499-1507.

D'ANTONI, J.M., A.K. MISHRA and H. JOO (2012): Farmers' perception of precision technology: The case of autosteer adoption by cotton farmers. In: Computers and Electronics in Agriculture 87: 121-128.

DABERKOW, S.G. and W.D. MCBRIDE (2003): Farm and Operator Characteristics Affecting the Awareness and Adoption of Precision Agriculture Technologies in the US. In: Precision Agriculture 4 (2): 163-177.

DOHMEN, T., A. FALK, D. HUFFMAN, U. SUNDE, J. SCHUPP and G.G. WAGNER (2011): Individual risk attitudes: Measurement, determinants, and behavioral consequences. In: Journal of the European Economic Association 9 (3): 522-550.

EL BENNI, N., R. FINGER and M.P. MEUWISSEN (2016): Potential effects of the income stabilisation tool (IST) in Swiss agriculture. In: European Review of Agricultural Economics 43 (3): 475-502.

EUROPEAN PARLIAMENT (2018): Infographic: how climate change is affecting Europe. https://www.europarl.europa.eu/news/en/headlines/society/20180905STO11945/infographic-how-climate-change-is-affecting-europe, call: 9.8.2022.

FEDERAL STATISTICAL OFFICE OF GERMANY (2019): Statistisches Jahrbuch 2019. https://www.destatis.de/DE/Themen/Querschnitt/Jahrbuch/jb-landforstwirtschaft, call: 21.1.2022.

GÖMANN, H., A. BENDER, A. BOLTE, W. DIRKSMEYER, H. ENGLERT, J.-H. FEIL, C. FRÜHAUF, M. HAUSCHILD, S. KRENGEL, H. LILIENTHAL, F.-J. LÖPMEIER, J. MÜLLER, O. MUßHOFF, M. NATKHIN, F. OFFERMANN, P. SEIDEL, M. SCHMIDT, B. SEINTSCH, J. STEIDL and K. STROHM (2015): Agrarrelevante Extremwetterlagen und Möglichkeiten von Risikomanagementsystemen. Thünen Report No. 30. Johann Heinrich von Thünen-Institut. https://www.econstor.eu/handle/10419/111497, call: 6.6.2022.

GRIFFIN, T.W., N.J. MILLER, J. BERGTOLD, A. SHANOYAN, A. SHARDA and I. A. CIAMPITTI (2017): Farm's Sequence of Adoption of Information-intensive Precision Agricultural Technology. In: Applied Engineering in Agriculture 33 (4): 521-527.

GRILLAKIS, M.G. (2019): Increase in severe and extreme soil moisture droughts for Europe under climate change. In: The Science of the total environment 660: 1245-1255.

GUZMAN-CASTILLO, M., S. BRAILSFORD, M. LUKE and H. SMITH (2015): A tutorial on selecting and interpreting predictive models for ordinal health-related outcomes. In: Health Services and Outcomes Research Methodology 15 (3-4): 223-240.

HARKNESS, C., M.A. SEMENOV, F. AREAL, N. SENAPATI, M. TRNKA, J. BALEK and J. BISHOP (2020): Adverse weather conditions for UK wheat production under climate change. In: Agricultural and Forest Meteorology 282: 107862.

HARRISON, G.W., M.I. LAU and E.E. RUTSTRÖM (2007): Estimating Risk Attitudes in Denmark: A Field Experiment. In: Scandinavian Journal of Economics 109 (2): 341-368.

HARTOG, J., A. FERRER-I-CARBONELL and N. JONKER (2002): Linking Measured Risk Aversion to Individual Characteristics. In: Kyklos 55 (1): 3-26.

ISGIN, T., A. BILGIC, D.L. FORSTER and M.T. BATTE (2008): Using count data models to determine the factors affecting farmers' quantity decisions of precision farming technology adoption. In: Computers and Electronics in Agriculture 62 (2): 231-242.

KIRK, A., F. MACMILLAN and N. WEBSTER (2010): Application of the Transtheoretical model to physical activity in older adults with Type 2 diabetes and/or cardiovascular disease. In: Psychology of Sport and Exercise 11 (4): 320-324.

KNAPP, T.R. (1990): Treating Ordinal Scales as Interval Scales: An Attempt To Resolve the Controversy. In: Nursing Research 39 (2): 121.

KOTSIRI, S., R.M. REJESUS, M.C. MARRA and M.M. VELANDIA (2011): Farmers' Perceptions about Spatial Yield Variability and Precision Farming Technology Adoption: An Empirical Study of Cotton Production in 12 Southeastern States. https://ageconsearch.umn.edu/record/98689/, call: 15.5.2022.

LEMKEN, D., A. SPILLER and M. von MEYER-HÖFER (2017): The Case of Legume-Cereal Crop Mixtures in Modern Agriculture and the Transtheoretical Model of Gradual Adoption. In: Ecological Economics 137: 20-28.

LORD, F.M. (1953): On the Statistical Treatment of Football Numbers. In: American Psychologist 8 (12): 750-751.

LUNT, T., A.W. JONES, W.S. MULHERN, D.P. LEZAKS and M.M. JAHN (2016): Vulnerabilities to agricultural production shocks: An extreme, plausible scenario for assessment of risk for the insurance sector. In: Climate Risk Management 13: 1-9.

MICHELS, M., W. FECKE, J.-H. FEIL, O. MUSSHOFF, J. PIGISCH and S. KRONE (2019): Smartphone adoption and use in agriculture: empirical evidence from Germany. In: Precision Agriculture 21 (2): 403-425.

MICHELS, M., C.-F. von HOBE and O. MUSSHOFF (2020): A trans-theoretical model for the adoption of drones by large-scale German farmers. In: Journal of Rural Studies 75: 80-88.

MISHRA, A.K. and H.S. EL-OSTA (2002): Managing risk in agriculture through hedging and crop insurance: what does a national survey reveal? In: Agricultural Finance Review 62 (2): 135-148.

MOSCARDI, E. and A. JANVRY (1977): Attitudes Toward Risk Among Peasants: An Econometric Approach. In: American Journal of Agricultural Economics 59 (4): 710-716.

OTANI, H., S.D. LEONARD, V.L. ASHFORD, M. BUSHROE and G. REEDER (1992): Age differences in perception of risk. In: Perceptual and Motor Skills 74 (2): 587-594.

OWUSU-SEKYERE, E., H. HANSSON and E. TELEZHENKO (2022): Use and non-use values to explain farmers' motivation for the provision of animal welfare. In: European Review of Agricultural Economics 49 (2): 499-525.

PAUSTIAN, M. and L. THEUVSEN (2017): Adoption of precision agriculture technologies by German crop farmers. In: Precision Agriculture 18 (5): 701-716.

PIERPAOLI, E., G. CARLI, E. PIGNATTI and M. CANAVARI (2013): Drivers of Precision Agriculture Technologies Adoption: A Literature Review. In: Procedia Technology 8: 61-69.

PROCHASKA, J.O. and W.F. VELICER (1997): The transtheoretical model of health behavior change. In: American journal of health promotion (AJHP) 12 (1): 38-48.

ROBERTS, R.K., B.C. ENGLISH, J.A. LARSON, R.L. COCHRAN, W.R. GOODMAN, S.L. LARKIN, M.C. MARRA, S.W. MARTIN, W.D. SHURLEY and J.M. REEVES (2004): Adoption of Site-Specific Information and Variable-Rate Technologies in Cotton Precision Farming. In: Journal of Agricultural and Applied Economics 36 (1): 143-158.

ROSE, D.C., W.J. SUTHERLAND, C. PARKER, M. LOBLEY, M. WINTER, C. MORRIS, S. TWINING, C. FFOULKES, T. AMANO and L.V. DICKS (2016): Decision support tools for agriculture: Towards effective design and delivery. In: Agricultural Systems 149: 165-174.

SCHAPER, C., H. BRONSEMA, L. THEUVSEN, H. MÜLLER and I. ROTTWILM (2012): Betriebliches Risikomanagement in der Landwirtschaft-eine empirische Analyse in Sachsen, Sachsen-Anhalt, Thüringen und Mecklenburg-Vorpommern. In: Landesamt für Umwelt, Landwirtschaft und Geologie 36.

SOK, J., J.R. BORGES, P. SCHMIDT and I. AJZEN (2021): Farmer Behaviour as Reasoned Action: A Critical Review of Research with the Theory of Planned Behaviour. In: Journal of Agricultural Economics 72 (2): 388-412.

STEVENS, S.S. (1946): On the Theory of Scales of Measurement. In: Science 103 (2684): 677-680.

TAMIRAT, T.W., S.M. PEDERSEN and K.M. LIND (2018): Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. In: Acta Agriculturae Scandinavica, Section B — Soil & Plant Science 68 (4): 349-357.

TEY, Y.S. and M. BRINDAL (2012): Factors influencing the adoption of precision agricultural technologies: a review for policy implications. In: Precision Agriculture 13 (6): 713-730.

TIEDEMANN, T., G. BREUSTEDT and U. LATACZ-LOHMANN (2011): Risikoberücksichtigung in der nicht parametrischen Effizienzanalyse: Auswirkungen auf die Effizienzbewertung von deutschen Schweinemastbetrieben. In: German Journal of Agricultural Economics 60: 215-229.

VELANDIA, M., R.M. REJESUS, T O. KNIGHT and B.J. SHERRICK (2009): Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales. In: Journal of Agricultural and Applied Economics 41 (1): 107-123.

VERBEEK, M. (2008): A Guide to Modern Econometrics. 3rd edition. John Wiley & Sons, Chichester.

VIGANI, M. and J. KATHAGE (2019): To Risk or Not to Risk? Risk Management and Farm Productivity. In: American Journal of Agricultural Economics 101 (5): 1432-1454.

VROOM, V.H. and B. PAHL (1971): Relationship between age and risk taking among managers. In: Journal of Applied Psychology 55 (5): 399-405.

WAPPNET (2020): Wappnet Agrar. https://www.risikoeinblick.de/wappnet-agrar/, call: 21.1.2022.

WATCHARAANANTAPONG, P., R.K. ROBERTS, D.M. LAMBERT, J.A. LARSON, M. VELANDIA, B.C. ENGLISH, R.M. REJESUS and C. WANG (2014): Timing of precision agriculture technology adoption in US cotton production. In: Precision Agriculture 15 (4): 427-446.

WILLITS, F.K., G.L. THEODORI and A.E. LULOFF (2016): Another look at Likert scales. In: Journal of Rural Social Sciences 31 (3): 126-139.

ZHENG, S., Z. WANG and C.J. WACHENHEIM (2019): Technology adoption among farmers in Jilin Province, China. In: China Agricultural Economic Review 11 (1): 206-216.

Acknowledgements

We thank the anonymous reviewers and the editor for helpful comments on an earlier version of this manuscript.

Contact author:
JULIA B. BLOCK
Georg-August-Universität Göttingen, Department of Agricultural Economics and Rural Development
Platz der Göttinger Sieben 5, 37073 Göttingen, Germany
e-mail: juliabarbara.block@uni-goettingen.de

Appendices

Appendix A

Introduction to the fictitious digital RMT (translated from German into English)

We will first introduce to you a possible digital RMT that you can use on your computer as well as on your smartphone and tablet:
In the fictitious RMT, a variety of possible risk factors are available for selection. With the help of step-by-step instructions, you can assess not only existing and current situations, but also future plans and first ideas.

In the first step, you typify your company by choosing between e.g. growth companies, family companies or branded companies. For better comprehension, all items are accompanied by explanatory information. The next level has categories such as location, consumer, legislator or food industry, from which you can spontaneously select subordinate influencing factors which are suitable for your business. After that, you name your concrete project and select risk factors from categories (e.g. failure of technology, lack of know-how in handling, permanent high stress level) that could threaten the achievement of the project now or in future. One step further, you can rank the already selected risk factors according to their importance. You can also enter here for each risk factor whether it has an effect on assets, liquidity, health and reputation. In addition, you can estimate the probability of damage in percent of a risk factor and the amount of damage in euros, as well as measures against the risk factors. At the end, you can read off the weighted risk factors with their ratings for your project from a well-structured table. The result is generated exclusively by your own inputs and evaluations or by third parties whom you may have asked to evaluate your risk management with the help of the programme.

In the next step, we present you statements that relate to the digital RMT described above. You will be asked to indicate the level of your agreement.

Appendix B

Question for the TTMU (translated from German into English)

Which statement are you most likely to agree with?

◯ The use of a digital RMT is currently of no benefit to me.

◯ The use of a digital RMT could currently be useful for me.

◯ The use of a digital RMT could currently be of great benefit to me.

◯ The use of a digital RMT is certainly of great benefit to me at the moment.

Appendix C

Question for the importance of digital support tools in the next 10 years (translated from German into English)

How important will adapting to digital farming and using digital support tools be to you within the next 10 years, in terms of your farm's profitability?
Please select a box on the scale from 1 to 5.

◯ 1 (not at all important)

◯ 2 (rather not important)

◯ 3 (I do not know)

◯ 4 (rather important)

◯ 5 (very important)

Appendix D

Table A1. Results of the ordinal logistic regression for the TTMU (N = 160)[a)]

Variable	Coefficient	S.E.	[95% - Confidence interval]
Age	0.014	0.016	[-0.017; 0.044]
Education	0.611	0.380	[-0.134; 1.357]
Full_Time	0.247	0.362	[-0.463; 0.957]
Farm_Size	0.0003	0.0004	[-0.0006; 0.0011]
Soil_Quality	-0.0201	0.0101	[-0.0400; -0.0003]
Rented_Land	0.010	0.007	[-0.003; 0.023]
Mobile_Devices	1.139	0.372	[0.410; 1.868]
Importance_Future [b)]	0.714	0.195	[0.331; 1.097]
Likelihood ratio test (χ^2)	42.60 ($p < 0.001$)		
Log likelihood value	-125.124		
McFadden Pseudo-R^2	0.146		

S.E. = Standard error
[a)] Dependent variable is TTMU; Stage 3 and 4 were combined in accordance with the Brant test for the parallel regression assumption.
[b)] 5-point Likert-scale (1 = not important; 5 = very important)
Source: Own data and calculations.

Appendix E

Table A2. Predicted probabilities and marginal effects (N = 160)[a)]

	TTMU = 1	TTMU = 2	TTMU = 3
Predicted probability	0.249	0.673	0.078
Variable		**Marginal effects** [b)]	
Age	-0.003	0.002	0.001
Education	-0.113	0.069	0.045
Full_Time	-0.046	0.028	0.018
Farm_Size	-0.00005	0.00003	0.00002
Soil_Quality	0.004	-0.002	-0.001
Rented_Land	-0.002	0.001	0.001
Mobile_Devices	-0.203	0.114	0.090
Importance_Future [c)]	-0.133	0.082	0.051

[a)] Dependent variable is TTMU; Stage 3 and 4 were combined in accordance with the Brant test for the parallel regression assumption.
[b)] The sign change between the Pre-Contemplation stage (TTMU = 1) and the Contemplation stage (TTMU = 2) suggests that variables with a considerable effect make a difference between farmers thinking digital RMTs are not useful and farmers thinking digital RMTs could be useful.
[c)] 5-point Likert-scale (1 = not important; 5 = very important)
Source: Own data and calculations.