Algorithm Aversion in Farmers' Intention to Use Decision Support Tools in Crop Management

Anna Massfeller*[1], Daniel Hermann[1], Alexa Leyens[1], Hugo Storm[1]

[1]Institute for Food and Resource Economics, University of Bonn, Germany

Contributed Paper prepared for presentation at the 99th Annual Conference of the Agricultural Economics Society, Bordeaux School of Economics, University of Bordeaux, France

14 – 16 April 2025

*anna.massfeller@ilr.uni-bonn.de, Meckenheimer Allee 174, 53115 Bonn, Germany

This work has been funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2070 – 390732324.

Abstract

Novel artificial intelligence (AI)-based decision support tools (DSTs) promise to make pesticide application more efficient. However, the adoption of existing, non-AI, DST by farmers is low, and farmers seem to prefer recommendations from human advisors. Additionally, for medical applications, there is evidence of users' reluctance against (potentially superior) AI-based recommendations - a phenomenon known as Algorithm Aversion. This study is the first to investigate Algorithm Aversion in the farming context specifically with respect to farmers' intention to use an AI-DST for wheat fungicide application. We conducted a preregistered online survey with a representative sample of German farmers in autumn 2024. The analysis is based on a novel Bayesian probabilistic programming workflow for experimental studies. The approach allows jointly analysing an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT) with a willingness-to-pay-experiment. We find that Algorithm Aversion plays an important role in farmers' decision-making. Our results emphasize the importance of user-friendly tech design, inform extension services on resource allocation, and stress the need for policy to support AI-DST adoption. This is the first study quantifying Algorithm Aversion in farmers' decision-making. It forms the foundation for future research on the underlying causes of Algorithm Aversion. Additionally, we show how probabilistic programming can improve experimental research.

Keywords Farmer Decision-Making, Algorithm Aversion, Decision Support Systems, Experiment, Bayesian Probabilistic Programming

JEL code Q16 R&D, Agricultural Technology, Biofuels, Agricultural Extension Services, Q18 Agricultural Policy, Food Policy, Animal Welfare Policy, D83 Search; Learning; Information and Knowledge; Communication; Belief

1. Introduction

Reducing pesticide use in intensive agricultural production is among the main goals of the current Common Agricultural Policy of the EU (European Commission, 2020), as their usage is closely related to damage to the ecosystem (Brühl et al., 2022; Geiger et al., 2010; Sharma et al., 2019). At the same time, pesticide use allows farmers to produce high yields and product quality (Oerke, 2006), contributing to food security (Schneider et al., 2023).

To improve pesticide application efficiency and effectiveness, farmers can use decision support tools (DST) (Lázaro et al., 2021). These tools help to optimize decisions under complex and uncertain conditions (Rose et al., 2016; Shtienberg, 2013). Novel artificial intelligence (AI)-based DST exhibit enhanced data gathering and prediction abilities by considering real-time conditions (e.g. infestation pressures), thereby promising to deliver improved recommendations for efficient pesticide application (Gautron et al., 2022; Khanna et al., 2024; Lázaro et al., 2021).

Realizing these potential positive economic and environmental effects hinges on farmers' willingness to adopt such tools. Previous research revealed that most farmers prefer recommendations from advisory services and other farmers over those from smartphone applications (Gabriel and Gandorfer, 2022; Genius et al., 2014; Kiraly et al., 2023; Skaalsveen et al., 2020). Thus, adoption of DST is often lower than expected (Heidrich, 2020; McCown, 2002; Rojo-Gimeno et al., 2019; Rose et al., 2016).

Such reluctance against (potentially superior) recommendations from algorithmic decision support is known as *Algorithm Aversion* (Dietvorst et al., 2015): the phenomenon of individuals preferring advice from humans over advice from an algorithm, even if the algorithm outperforms the human. While this phenomenon is well-studied in other contexts like medicine (Longoni et al., 2019) or finance (Cohen et al., 2021), it is not studied in context of agricultural decision-making (Mahmud et al., 2022). However, with the ongoing development of AI-based DST in crop production (Gautron et al., 2022) and their potential for improving efficient pesticide usage to decrease environmental degradation (Geiger et al., 2010), there is a crucial need for understanding farmers' decision to use such advanced technologies. Therefore**,** we aim to explore and quantify the role of Algorithm Aversion in farmers' intention to adopt AI-based DST for pesticide application, adding to the literature on the adoption of digital technologies.

We focus on the specific case of fungicide application in wheat. Fungi in wheat are responsible for 15-20% yield loss per year (Figueroa et al., 2018) and impacts increase with intensification of crop productivity (Oerke, 2006). In Germany, a country known for highly intensive crop production, fungicides account for 24% of pesticide sales (in t) in 2022. As a result, German wheat yields are among the highest worldwide (Gianessi and Williams, 2011; Oerke, 2006). Nevertheless, fungicide usage is closely linked to environmental degradation, e.g., biodiversity loss (Fritsch et al., 2024; Geiger et al., 2010; McMahon et al., 2012). As part of Directive 2009/128/EC on the sustainable use of pesticides (European Commission, 2009), EU farmers are obliged to follow the guidelines of integrated pest management (IPM) (European Commission, 2024; Smith and Van den Bosch, 1967). Within these guidelines, pesticide usage is recommended only after curative measures have been applied and if a certain infestation threshold is reached.

DSTs for fungicide application show the potential to halve fungicide use without increasing the disease risk, compared to calendar-based strategies (Lázaro et al., 2021). This effect can be mainly traced back to the DSTs' ability to predict spray timing based on observed or predicted risk of disease, leading farmers to apply the fungicides when they are most effective during the growing season. In recent years, AI-based DST relying on reinforcement learning and using real-time data from in-field sensors or drones evolved (Gautron et al., 2022) and a meta-study by Rossi et al. (2019) shows that out of 217 DST for fungicide application, the majority is for wheat. Additionally, newest developments show the combination of AI-DST for fungi in wheat with novel insurance systems ensuring farmers' compensation if the followed recommendation fails (BASF, 2024).

In order to answer our research question, we conducted a pre-registered online survey[1] with German arable farmers in autumn 2024 consisting of 1) a theory-based part extending the Unified Theory of Acceptance and Usage of Technology (UTAUT) (Venkatesh et al., 2003) and 2) an experiment aiming at eliciting the farmers' Willingness-To-Pay (WTP) for hypothetical recommendations coming from an AI-based DST versus one coming from a human advisor. In the preparation and analysis of the study, we follow a probabilistic programming (PP) workflow (Gelman et al., 2020; McElreath, 2020; Storm et al., 2024) which offers advantages for survey design and analysis. Specifically, it allows us to jointly analyze

[1] Please find the public, anonymous pre-registration here:
https://osf.io/hkwn4/?view_only=8b49f507a39a40e881483d194a6bb445

the UTAUT and WTP part of the survey in one combined analysis. It improves the transparency of the underlying theoretical assumption and allows for code testing, model inference, and the illustration of the results using synthetic data before actual data collection (see pre-registration). Lastly, it provides the advantages of the Bayesian approach to interpret uncertainty compared to frequentist approaches (Storm et al. (2024). To our knowledge, we are among the first to present an application of the Bayesian workflow covering all stages of the experimental study (see Stranieri et al. (2022) or Varacca (2024) for other applications of the Bayesian approach in experimental settings).

Our results indicate that Algorithm Aversion plays an important role in farmers’ intention to use and willingness to pay for AI-DST. With this study, we contribute to the existing literature in three ways. First, we are the first to examine and quantify the role of Algorithm Aversion in farmers’ decision-making. Second, we show how the probabilistic workflow can be used to develop and analyze experimental surveys. Third, we provide valuable insights for tech developers, policymakers, and agricultural extension services on how to bring together farmers and AI-based DST that have the potential to improve pesticide application efficiency.

2. Conceptual Framework

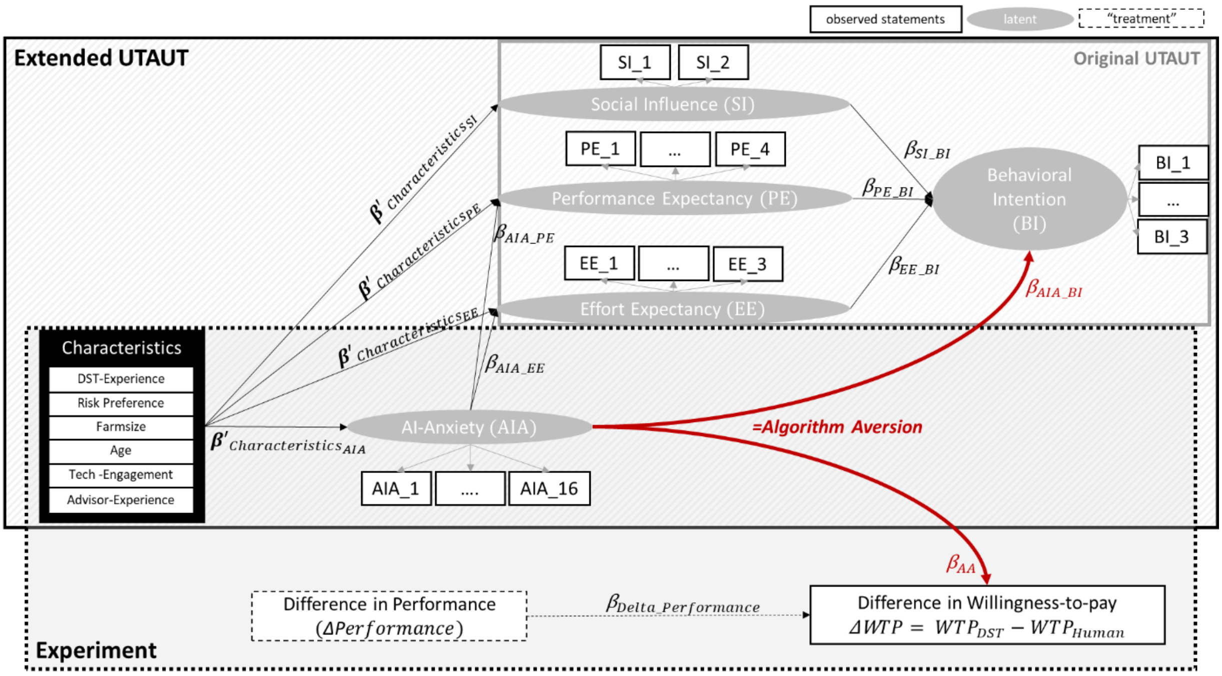
In order to test our hypothesis and to answer our research question, we first need to conceptualize Algorithm Aversion to make it measurable. To this end, we follow the PP workflow (Storm et al., 2024) and in the first step, define the quantity to estimate as the extent of Algorithm Aversion.

The role of novel technologies’ performance as important vehicle for its adoption has already been studied in similar contexts. For example, recent studies based on the UTAUT found that, among others, Performance Expectancy and attitude towards the technology are positively related to the farmers’ behavioral intention to adopt (Giua et al., 2022; Michels et al., 2020; Rübcke von Veltheim et al., 2022) and trust in robots and AI is mainly explained by their performance, transparency, and reliability (Hancock et al., 2011; Kaplan et al., 2023).

Thus, as performance seems to play a major role in trust in AI and hence for adoption decisions and in line with the definition by Dietvorst et al. (2015), within our study, we focus on performance as a major vehicle to elicit farmers' intention to use DSTs. This focus is also reflected in the choice of the UTAUT by Venkatesh et al. (2003) as a theoretical basis, as this framework allows us to specifically consider Performance Expectancy as a construct explaining the intention to use a technology.

In the second step of the workflow, we proceed by defining a causal model, depicted in a directed acyclic graph (DAG), Figure 1. Our study consists of two parts: the extended UTAUT-based approach (upper part Figure 1) and the WTP experiment (lower part Figure 1). In the following, we explain the conceptualization of Algorithm Aversion for each of these parts.

Figure 1: Directed Acyclic Graph

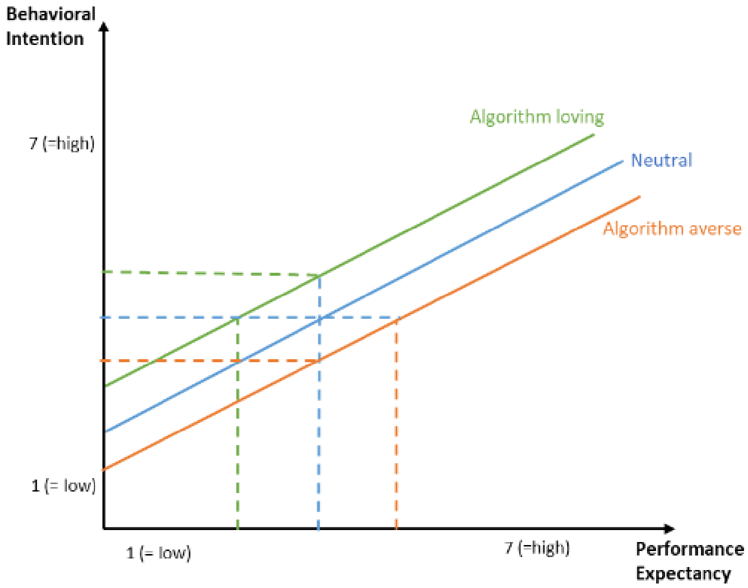


2.1. *Conceptualization of Algorithm Aversion within UTAUT*

To reflect the role of Algorithm Aversion within the UTAUT and, in contrast to Cao et al. (2021), who pursued a similar approach, we extend the traditional setup by adding "AI-Anxiety" as a novel construct, as shown in the DAG in Figure 1. This construct is formed based on a validated AI-Anxiety scale from Wang and Wang (2022). We use 16 of their statements to capture each individual's AI-Anxiety (i.e. $AIA_1 - AIA_{16}$). Following Kaplan et al. (2023), who found that ability- and characteristic-based factors explain trust in AI, and Mahmud et al. (2022), who identified personal factors to explain Algorithm Aversion, we assume that AI-Anxiety is, similar to the other constructs, a function of the personal characteristics. For more details on the choice of personal characteristics and the relation between the constructs and respective UTAUT-based hypotheses, please see the pre-registration.

We graphically depict the effect of β_{AIA_BI} in Figure 2. Algorithm Aversion would occur if farmers exhibit a low behavioral intention to use an AI-based DST although the performance expectancy is high, resulting in a negative value for β_{AIA_BI}, respectively. This means that for a certain level of performance expectancy on the 7-point Likert scale, a neutral person (blue line in Figure 2) would exhibit a certain level of behavioral intention on the same scale. In the case of an algorithm averse person (orange line), the “translation” from performance expectancy into behavioral intention would be distorted by Algorithm Aversion. Hence, for the same level of performance expectancy the behavioral intention would be lower compared to a neutral person. This means that a negative β_{AIA_BI} materializes as a downward shift of the line for individuals with high AI-Anxiety.

Figure 2: UTAUT-based conceptualization of Algorithm Aversion

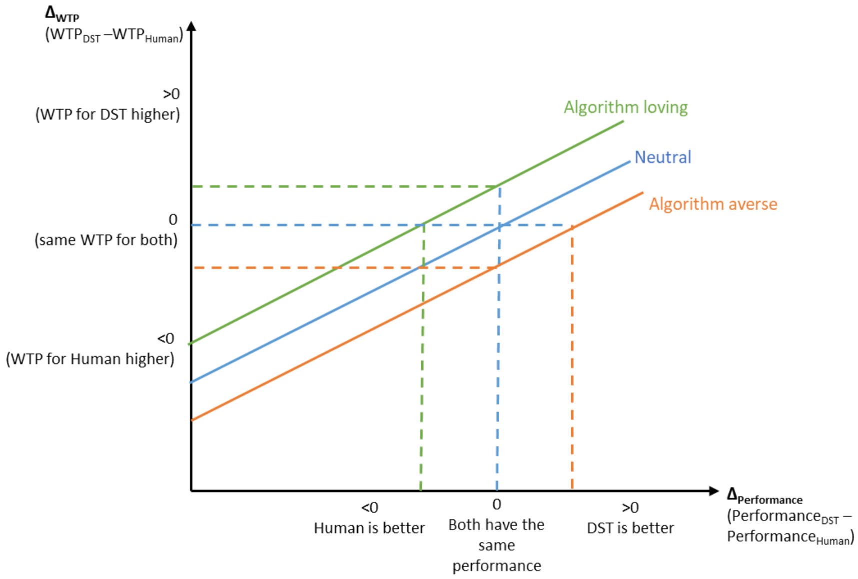


2.2. *Conceptualization of Algorithm Aversion in the Experiment*

In the second part of the survey, we conduct a willingness-to-pay (WTP) experiment (lower part Figure 1). More specifically, we elicit the difference in the WTP for human and AI-based DST advice (ΔWTP) given information on the difference in the performance ($\Delta Performance$) of each (for a detailed description of “performance” see section 3.1). As depicted in Figure 3, we assume that if the human and the AI-DST perform equally well (i.e. $\Delta Performance = 0$), for an algorithm-neutral person (blue line), there would be no difference in the WTP, i.e., $\Delta WTP = 0$. Consequently, if the human performs better, the WTP for the human is higher, and vice versa. In contrast, an algorithm averse person (orange line) would exhibit a higher WTP for the human, even if the AI-DST performs equally well or even better. From this setup, it follows that, similar to the UUTAUT setup we assume Algorithm Aversion to materialize as the negative effect of AI-Anxiety on ΔWTP, called β_{AA} (lower red arrow in

Figure 1) which translates into a downward shift of the lines in Figure 3 for individuals with high AI-Anxiety.

Figure 3: Conceptualization of Algorithm Aversion on the Experiment



3. Method and Data

3.1. Survey Design, Sampling and Data

We conducted a three-step online survey in cooperation with a market research company. The survey was carried out by German arable farmers and collected quantitative primary data in autumn 2024. We obtained ethical clearance before the survey started, pretested it with experts and farmers, and preregistered it on the open science framework[2]. Before participating, farmers had to accept the data protection rules and meet the criteria of being engaged in arable farming. Participating farmers were informed upon the survey that they could voluntarily participate in a lottery at the end. In this lottery, about 2% of farmers were randomly drawn and received either a voucher or a non-cash price. To establish a baseline definition of AI-based DST among participants, the questionnaire began with a short neutral information text about DST and what we understand as AI-based tools. Then the order of the two parts (UTAUT-based statements and experiment) was randomly assigned between participants.

In the UTAUT-based part, participants had to evaluate statements for each of the latent constructs on a 7-point Likert-Scale (1= Totally disagree, 3 = Neutral, 7 = Totally agree). We formulated the statements following 1) the original formulation as proposed by Venkatesh et

[2] https://osf.io/hkwn4/?view_only=8b49f507a39a40e881483d194a6bb445

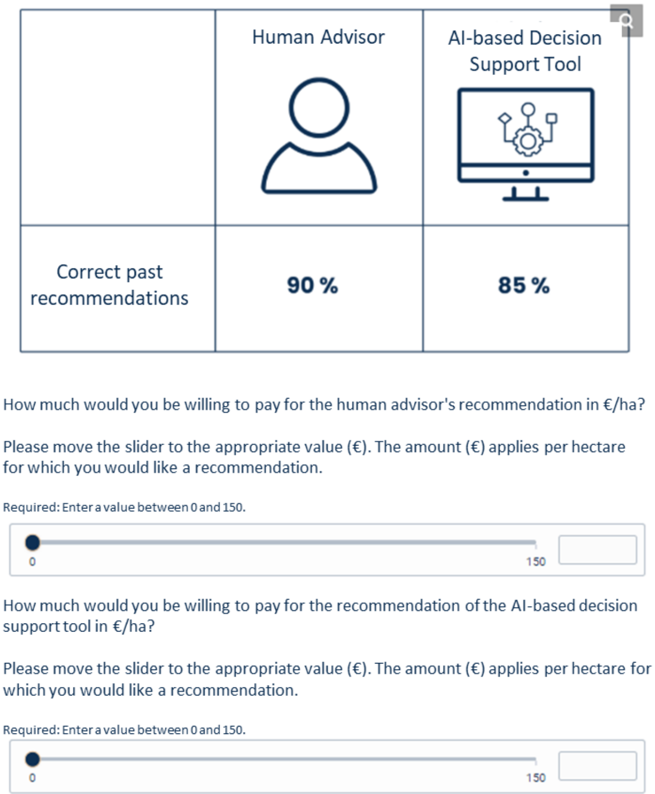
al. (2003) and 2) modifications from similar studies with German farmers (Michels et al., 2020; Otter and Deutsch, 2023; Rübcke von Veltheim et al., 2022). A novelty compared to existing studies was the evaluation of statements on AI-Anxiety based on the validated AI-Anxiety scale from Wang and Wang (2022).[3]

The experimental part of the survey is an adaptation from a study from the medical context done by Longoni et al. (2019). We transferred this study to the agricultural decision-making context and adjusted it to fit our purpose. As a first step, we showed all participants a short text about fungicide applications, reminded farmers of the threshold principle of Integrated Weed Management (IWM), and informed them about the two options for advice. We clearly stated that except for the subject analyzing the data and making the recommendation (human advisor or AI-DST), everything else was the same (input data needed, time to receive the recommendation, etc.). Each farmer was then shown the actual WTP choice (Figure 4) three times, with varying values for past performance. We define performance as the probability of an improvement in the economic result compared to the status quo, i.e. without this additional advice.[4] Out of nine possible combinations (85%,90%, and 95% for each), three combinations were chosen, whereby the human advisor values were drawn without replacement (i.e., each performance value was shown once) while the ones for the AI-DST were randomly drawn with replacement. The slider to choose the monetary value willing to spend was, by default, set at 0.

[3] Traditionally, such theory-based approaches are analyzed using a Partial Least Squares Structural Equation Model (PLS-SEM). In the final paper we will compare our results from Bayesian statistics to the results obtained from the traditional PLS-SEM approach and examine the relation between constructs (outer model) and within statements (inner model), but this aspect is not within the scope of the present conference contribution.

[4] In the survey this read as follows (translated from German): *"We will [also] show you how successful the recommendations have been in the past. This means you will see how often the recommended strategy led to reduced yield losses when the recommendation was followed exactly. Example: In the past, advice X has recommended the correct fungicide strategy 90% of the time. This means that in 9 out of 10 cases, advice X recommended a fungicide strategy that led to an improvement in the economic result compared to the status quo (your previous management), i.e. without this additional advice."*

Figure 4: WTP Choice Design



3.2. Statistical Framework

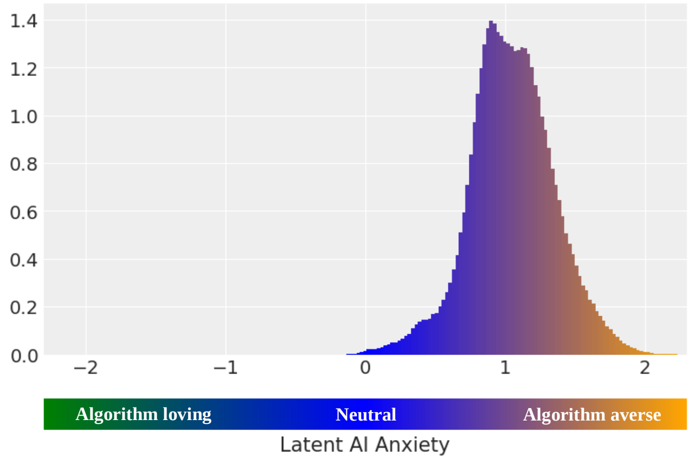
In the third step of the PP workflow, we use the DAG to define the statistical model and the Data Generating Process (DGP) by describing theory-based distributional and relational assumptions on the model parameters. While details can be found in the pre-registration, one important aspect is the Bayesian modeling of Likert-Scale items to measure latent constructs. Based on Item-Rating-Theory (Andersen, 1997; Andrich, 2016), we follow seminal works from Fox (2010), Stranieri (2022), and Varacca (2024) in the modeling of cut points for the Likert-scale-type responses and the choice of priors. Another important aspect of the approach is that it allows estimating the parameter of the UTAUT and the WTP experiment in one step, while also estimating the latent AI-Anxiety (AIA in Figure 1) from both parts of the survey.

In the next step of the PP workflow, we create synthetic data based on the DGP and use this data to test if our statistical model can recover the deliberately set values for Algorithm Aversion. This procedure allows us to test our model's functionality and simulate how farmers might complete the survey, which enables improving survey design before data collection. The results of this step can be found in the pre-registration. As last step, we analyze the real data obtained from the survey using the DGP. Note that the model is allowed to learn from the data and update the prior beliefs.

4. Results

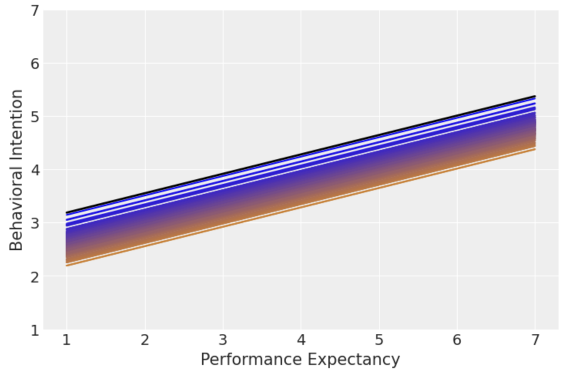
In our preliminary results, we find that within our representative sample of 250 German arable farmers, Algorithm Aversion plays an important role in the intention to use and the WTP for AI-DST. We find that both coefficients of interest (β_{AIA_BI} and β_{AA}) are clearly negative, with a mean of -0.56 for β_{AIA_BI} (Credibility Interval 5%-95% [-1.03; 0.00]) and a mean of -0.35 for β_{AA} (Credibility Interval 5%-95% [-0.40; -0.31]). Following our conceptualization of Algorithm Aversion (Figures 2 and 3 in Section 2), we present the results of the UTAUT part and the experiment. As shown in Figure 5, farmers in our sample are quite clearly algorithm anxious (i.e. Latent AI-Anxiety > 0). We depict AI-neutral individuals in blue and AI-anxious ones in yellow.

Figure 5: Distribution of latent AI-Anxiety within sample

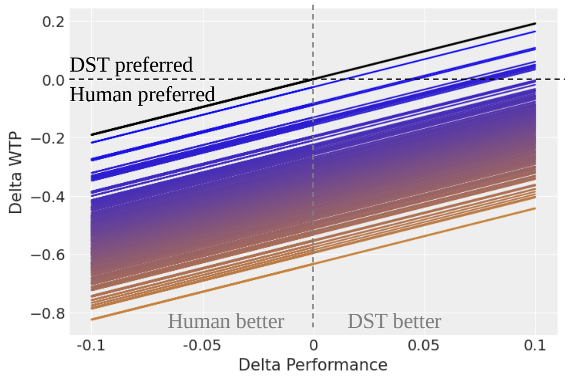


In Figure 6, we now turn to the relationship between Performance Expectancy and Behavioral Intention (UTAUT part, left side) and between Performance and WTP (experiment, right side) for different levels of AI-Anxiety.

Figure 6: Regression lines for UTAUT-part (left) and experiment (right)



Note: Effort Expectancy and Social Influence are kept at their means. The black line depicts an algorithm-neutral individual.



Note: Positive Delta-Performance indicates that the AI-DST performs better, negative that the human performs better. Similarly, positive values for Delta-WTP indicate a higher WTP for the AI-DST and negative values a higher WTP for the human. The black line depicts an algorithm-neutral individual.

For both parts, a downward shift of the lines for individuals with higher AI-Anxiety (yellowish lines) indicates the presence of Algorithm Aversion. The left plot shows the relation between Performance Expectancy and Behavioral Intention. It can be seen that in general, the Behavioral Intention to adopt an AI-based DST is rather low. With increasing levels of Performance Expectancy, Behavioral Intention increases, indicating a positive relationship between these two constructs. Related studies relying on the UTAUT as a theoretical framework found a similar positive relationship between Performance Expectancy and Behavioral Intention (Giua et al., 2022; Michels et al., 2020; Otter and Deutsch, 2023; Rübcke von Veltheim et al., 2022). With increasing AI-Anxiety, the lines are shifting downwards, indicating that AI-anxious individuals (yellowish lines) have a lower Behavioral Intention at the same Performance Expectancy level as algorithm-neutral individuals (blue).

The right plot shows a similar pattern for the experiment. At a given performance difference level, algorithm-anxious individuals exhibit a lower WTP for AI-DST. More concretely, even if the AI-DST performs better than the individual, AI-anxious individuals prefer the human advisor.

When comparing our results to the ones from Longoni et al. (2019) in the medical context, similar observations were made: participants preferred the human healthcare provider over the AI-automated one, even if it performed worse. Similarly, participants were willing to pay more for a human provider than for an AI-automated one.

To summarize, we find that the overall Behavioral Intention to adopt, as well as the WTP for AI-DST, is rather low within our sample. While even algorithm-neutral individuals seem to be rather skeptical towards such tools, there is a clear trend of algorithm-anxious people exhibiting an even lower Intention/ WTP at a given Performance (Expectancy) level, indicating that Algorithm Aversion plays an important role.

5. Discussion

In the following, we discuss potential factors explaining Algorithm Aversion for our sample of German arable farmers, grouped into 1) algorithm-related, 2) individual-related, and 3) task-related factors, based on the framework by Mahmud et al. (2022).

5.1. Algorithm-related factors explaining Algorithm Aversion

The first group of factors, algorithm-related ones, consists of design, decision, and delivery factors. One main reason for Algorithm Aversion is the black-box nature of the tool, indicating a lack of transparency (Dzindolet et al., 2002). Accessibility and understandability of the recommendation are important to reduce Algorithm Aversion (Chander et al., 2018). The missing access to the algorithms' reasoning leads to reduced trust in the recommendation (Önkal et al., 2009), especially if the recommendation contradicts one's own decision (Festinger, 1957). This is in line with findings on farmers' non-AI DST adoption, where transparency about the algorithm and reasoning of recommendations explains trust in the tool and hence adoption by farmers (Akaka et al., 2024; Kerebel et al., 2013; Rose et al., 2016). We assume this black box character and lack of transparency and trust leads to doubting the accuracy of the recommendation resulting in several fears among farmers inducing Algorithm Aversion.

First, individuals might fear the AI-DST to overlook their unique characteristics and provide generic recommendations, a phenomenon termed "uniqueness neglect" (Longoni et al., 2019). In the agricultural context, farmers seem to be more influenced by peers who face the same local production conditions (e.g., soil quality, topography) as those unique conditions matter for farm management decisions (Massfeller and Storm, 2024).

A second fear is not only related to the algorithm but also the outlook, that is, the gain or loss prospect of the decision. The reliance on the algorithmic recommendation seems to depend on whether a gain or a loss is forecasted (Mahmud et al., 2022) but is also closely related to the risk tolerance of the individual (Swinney, 1999). Within our sample, most farmers perceive themselves as neither extremely risk-averse nor extremely risk-loving. However, in the case of pesticide application, farmers seem to (over-)emphasize the risk of yield loss due to a fungal infection or weed infestation (Gent et al., 2011; McRoberts et al., 2011; Möhring and Finger, 2017; Skevas et al., 2014). Known as loss aversion and rooted in Prospect Theory (Kahneman and Tversky, 2013), this phenomenon can result in risk-mitigating behavior. Farmers might fear, that an AI-DST does not take the long-term risks into account, leading to distrust in the recommendation (Macé et al., 2007).

5.2. Individual-related factors explaining Algorithm Aversion

Concerning the second group of individual-related factors, research in other contexts found that some individuals habitually exhibit a general aversion to algorithms, coming along with a general distrust and negative perceptions about the algorithmic decision (Mahmud et al., 2022). Related research on DST adoption decisions found farmers to be rather skeptical about the technologies (Akaka et al., 2024; Heidrich, 2020; McCown, 2002; Rojo-Gimeno et al., 2019; Rose et al., 2016). This is mirrored in our sample, where we find that most farmers exhibit a rather low technological interest. Similarly, other studies found that low technological interest (Rübcke von Veltheim et al., 2022) and a negative attitude towards the technology (Otter and Deutsch, 2023) explain a low intention to adopt. Hence, we conclude that a general, habitual aversion towards algorithms could explain our findings.

Another important personality trait related to Algorithm Aversion is the concern about the relationship with the human expert (Mahmud et al., 2022). Farm advisors are among the preferred sources of recommendation (Skaalsveen et al., 2020) and the relationship is often quite familiar and long-lasting (Kuehne et al., 2020). In our sample, the majority of farmers indicated they have had good to excellent experiences with their human advisor over the past 5 years. Farmers might fear jeopardizing this relationship when switching to AI-DST tools. For example, it was found that farmers wish to not replace but rather complement human advice with algorithmic advice (McCown, 2002; Rose et al., 2016). This finding is supported by results from Longoni et al. (2019) in the context of medical AI tools, where patients prefer a combination of human and AI healthcare providers.

When turning to prior experience with algorithms, in our case DST, this can influence Algorithm Aversion in both directions (Li et al., 2020; Liu et al., 2019). Within our sample, most farmers had rather bad experiences with (non-AI) DST, potentially resulting in reservations about the technology (Mahmud et al., 2022). Experience with algorithms also comes along with the ability to use and familiarity with algorithms, which plays an important role in their adoption (Khanna et al., 2024). While most farmers in our sample use some digital technology (e.g., digital accounting, section control, or variable rate application), the use of AI tools among a subsample of German farmers was found to be below 10% (Rohleder and

Meinel, 2024). Additionally, digital and AI training are closely related to age. Typically, the farming population is rather old; in our sample, the mean age is 50 years. Older farmers tend to feel less competent in using digital tools (Rübcke von Veltheim et al., 2022) and with increasing age, Algorithm Aversion increases in other decision-making contexts (Araujo et al., 2020; Lourenço et al., 2020), supporting our findings.

5.3. Task-related factors explaining Algorithm Aversion

The last group of factors considers the contextual setting of the task. From a social and cultural perspective, other peoples' views and experience of algorithms play a crucial role in Algorithm Aversion (Alexander et al., 2018; Workman, 2005). Within our sample, most farmers believe that neither their colleagues nor other farmer friends think one should use an AI-DST for fungicide application. Such injunctive norms have been found to be of critical importance in farmers' decision-making (see, e.g., overview by Déssart et al. (2019)). Similarly, descriptive norms, i.e., "Do I know or observe peers (successfully) using the new tool?" influence farmers' adoption decisions (Massfeller and Storm, 2024) but seem to play a minor role at the moment as AI-DST usage among farmers is low. In the context of pesticide application, social factors are closely related to the notion of what is considered a "good farmer" (Burton et al., 2020; Lavoie and Wardropper, 2021; Sutherland, 2013; Sutherland and Darnhofer, 2012; Westerink et al., 2021). As it has been found that individuals perceive those who use an algorithm as less capable and intelligent (Arkes et al., 1986; Diab et al., 2011; Eastwood et al., 2012), the same might apply to the agricultural context. Farmers want to signal their success in being a good farmer, for example by having tidy wheat fields without fungal diseases (Burton, 2012; Burton and Wilson, 2006; Davis and Carter, 2014; Dentzman and Jussaume, 2017; Lavoie and Wardropper, 2021; Marr and Howley, 2019). As discussed in Sections 4.2. and 4.3. the (perceived) risk of the algorithm not giving an accurate recommendation, taking (long-term) crop management effects into account, might not only trigger farmers' risk of yield loss but also their wish to be perceived as good farmers. As we assume farmers are not purely profit-maximizers but rather utility-maximizers, peer perception and social recognition might be equally important as high yield and healthy fields (Weersink and Fulton, 2020).

6. Conclusion

With this study, we are the first to explore and quantify the role of Algorithm Aversion in the agricultural decision-making context. Our result that Algorithm Aversion plays an important role is supported in both the UTAUT-based and the experimental part of the survey.

We present a novel approach of how following a probabilistic programming workflow can complement survey design and analysis.

For the final version of this paper, we aim to provide more details on the descriptive results. We further plan to compare our probabilistic programming UTAUT results to the traditional approach of partial least squares-structural equation modelling (PLS-SEM) and to dig deeper into the interpretation of the coefficients by testing the UTAUT-related hypotheses on the relation between the constructs.

One limitation of our study is the hypothetical character of the scenario. In line with the literature, we elicited farmers' stated preferences and not the incentivized WTP or on-farm adaptation decision. We believe that our work can serve as a basis for future studies on Algorithm Aversion focusing on real-world decisions and revealed preferences.

Given the increasing potential of AI-based DST for efficiency improvements in crop production, based on our findings, future research needs to consider the role of Algorithm Aversion in adoption studies and should investigate the reasons for it to identify paths for overcoming these challenges as well as potential policy support mechanisms.

We conclude that technology development needs to carefully design AI-DST by considering farmers' AA. It should probably not be the AI-DSTs' goal to replace humans but rather complement either advisors' recommendations or farmers' own reasoning (Evans et al., 2017; Hochman and Carberry, 2011; Rose et al., 2016).

Given the overall low intention and WTP for AI-DST, financial support from the policy side might be needed to convince farmers to use such novel tools. Further, given the strong preference for human advice, agricultural advisory services should carefully decide which tasks to outsource to AI and which to continue executing by human advisors.

References

Akaka, J. J., García-Gallego, A., Georgantzis, N., Tisserand, J.-C., Vasileiou, E., and Ramsden, M. (2024). Decision Support Systems adoption in pesticide management. *Open Research Europe 4*: 142.

Alexander, V., Blinder, C., and Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior 89*: 279–288.

Andersen, E. B. (1997). The rating scale model. *Handbook of Modern Item Response Theory* : 67–84.

Andrich, D. (2016). Rasch Rating-Scale Model. *Handbook of Item Response Theory* : 103–122.

Araujo, T., Helberger, N., Kruikemeier, S., and de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society 35*: 611–623.

Arkes, H. R., Dawes, R. M., and Christensen, C. (1986). Factors influencing the use of a decision rule in a probabilistic task. *Organizational Behavior and Human Decision Processes 37*: 93–110.

BASF. (2024). *xarvio HEALTHY FIELDS*. https://www.xarvio.com/de/de/products/healthy-fields.html , last accessed January 9, 2025.

Brühl, C. A., Zaller, J. G., Liess, M., and Wogram, J. (2022). The rejection of synthetic pesticides in organic farming has multiple benefits [Review of *The rejection of synthetic pesticides in organic farming has multiple benefits*]. *Trends in Ecology & Evolution 37*: 113–114. resp.llas.ac.cn , 113–114. http://dx.doi.org/10.1016/j.tree.2021.11.001 , last accessed

Burton, R. J. F. (2012). Understanding Farmers' Aesthetic Preference for Tidy Agricultural Landscapes: A Bourdieusian Perspective. *Landscape Research 37*: 51–71.

Burton, R. J. F., Forney, J., Stock, P., and Sutherland, L.-A. (2020). *The Good Farmer: Culture and Identity in Food and Agriculture*. Routledge.

Burton, R. J. F., and Wilson, G. A. (2006). Injecting social psychology theory into conceptualisations of agricultural agency: Towards a post-productivist farmer self-identity? *Journal of Rural Studies 22*: 95–115.

Cao, G., Duan, Y., Edwards, J. S., and Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation 106*: 102312.

Chander, Wang, J., Srinivasan, R., Uchino, K., and Chelian, S. (2018). *Working Beliefs: AI Transparency Enterprise, : IUI Workshops*.

Cohen, S. N., Snow, D., and Szpruch, L. (2021). Black-box model risk in finance. In *arXiv [q-fin.CP]*. arXiv. http://arxiv.org/abs/2102.04757 , last accessed

Davis, D., and Carter, J. (2014). Finding common ground in weed management: peri-urban farming, environmental and lifestyle values and practices in southeast Queensland, Australia. In *The Geographical Journal* (Vol. 180, Issue 4). , 342–352.

Dentzman, K., and Jussaume, R. (2017). The Ideology of U.S. Agriculture: How Are Integrated Management Approaches Envisioned? *Society & Natural Resources 30*: 1311–1327.

Déssart, F. J., Barreiro-Hurlé, J., and van Bavel, R. (2019). Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics 46*: 417–471.

Diab, D. L., Pui, S.-Y., Yankelevich, M., and Highhouse, S. (2011). Lay perceptions of selection decision aids in US and non-US samples. *International Journal of Selection and Assessment 19*: 209–216.

Dietvorst, B. J., Simmons, J. P., and Massey, C. (2015). Algorithm aversion: people erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology. General 144*: 114–126.

Dzindolet, M. T., Pierce, L. G., Beck, H. P., and Dawe, L. A. (2002). The perceived utility of human and automated aids in a visual detection task. *Human Factors 44*: 79–94.

Eastwood, J., Snook, B., and Luther, K. (2012). What people want from their professionals: Attitudes toward decision-making strategies. *Journal of Behavioral Decision Making 25*: 458–468.

European Commission. (2009). *Directive 2009/128/EC*. Brussels, Belgium: European Commission. http://data.europa.eu/eli/dir/2009/128/2009-11-25 , last accessed December 4, 2024.

European Commission. (2020). *Key policy objectives of the CAP 2023-27*. Agriculture and Rural Development. https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cap-2023-27/key-policy-objectives-cap-2023-27_en , last accessed December 5, 2024.

European Commission. (2024). *Integrated pest management (IPM)*. Food Safety. https://food.ec.europa.eu/plants/pesticides/sustainable-use-pesticides/integrated-pest-management-ipm_en , last accessed November 12, 2024.

Evans, K. J., Terhorst, A., and Kang, B. H. (2017). From Data to Decisions: Helping Crop Producers Build Their Actionable Knowledge. *Critical Reviews in Plant Sciences 36*: 71–88.

Festinger, L. (1957). A Theory of Cognitive Dissonance. *A Theory of Cognitive Dissonance 291*.

Figueroa, M., Hammond-Kosack, K. E., and Solomon, P. S. (2018). A review of wheat diseases—a field perspective. *Molecular Plant Pathology 19*: 1523–1536.

Fox, J.-P. (2010). *Bayesian item response modeling* , 2010th ed. [PDF]. New York, NY: Springer.

Fritsch, C., Berny, P., Crouzet, O., Le Perchec, S., and Coeurdassier, M. (2024). Wildlife ecotoxicology of plant protection products: knowns and unknowns about the impacts of currently used pesticides on terrestrial vertebrate biodiversity. *Environmental Science and Pollution Research International* .

Gabriel, A., and Gandorfer, M. (2022). *Landwirte-Befragung 2022 Digitale Landwirtschaft – Bayern*. Bayerische Landesanstalt für Landwirtschaft. https://www.lfl.bayern.de/mam/cms07/ilt/dateien/ilt6_dft_ergebnisband_by_2022_805.pdf , last accessed

Gautron, R., Maillard, O.-A., Preux, P., Corbeels, M., and Sabbadin, R. (2022). Reinforcement learning for crop management support: Review, prospects and challenges. *Computers and Electronics in Agriculture 200*: 107182.

Geiger, F., Bengtsson, J., Berendse, F., Weisser, W. W., Emmerson, M., Morales, M. B., Ceryngier, P., Liira, J., Tscharntke, T., Winqvist, C., Eggers, S., Bommarco, R., Pärt, T., Bretagnolle, V., Plantegenest, M., Clement, L. W., Dennis, C., Palmer, C., Oñate, J. J., … Inchausti, P. (2010). Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland. *Basic and Applied Ecology 11*: 97–105.

Gelman, A., Vehtari, A., Simpson, D., Margossian, C. C., Carpenter, B., Yao, Y., Kennedy, L., Gabry, J., Bürkner, P.-C., and Modrák, M. (2020). Bayesian Workflow. In *arXiv [stat.ME]*. arXiv. http://arxiv.org/abs/2011.01808 , last accessed

Genius, M., Koundouri, P., Nauges, C., and Tzouvelekas, V. (2014). Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. *American Journal of Agricultural Economics 96*: 328–344.

Gent, D. H., De Wolf, E., and Pethybridge, S. J. (2011). Perceptions of risk, risk aversion, and barriers to adoption of decision support systems and integrated pest management: an introduction. *Phytopathology 101*: 640–643.

Gianessi, L., and Williams, A. (2011). *Europe's wheat yields are the world's highest due to fungicide use*.

Giua, C., Materia, V. C., and Camanzi, L. (2022). Smart farming technologies adoption: Which factors play a role in the digital transition? *Technology in Society 68*: 101869.

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., de Visser, E. J., and Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors 53*: 517–527.

Heidrich, S. W. (2020). *Akzeptanz einer On-Line Anwendung zur landwirtschaftlichen Betriebsoptimierung als Entscheidungshilfe* , W. B. Christoph Pahmeyer, Ed. [Bachelor]. RHEINISCHE FRIEDRICH-WILHELMS-UNIVERSITÄT BONN .

Hochman, Z., and Carberry, P. S. (2011). Emerging consensus on desirable characteristics of tools to support farmers' management of climate risk in Australia. *Agricultural Systems 104*: 441–450.

Kahneman, D., and Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the Fundamentals of Financial Decision Making*. WORLD SCIENTIFIC , 99–127.

Kaplan, A. D., Kessler, T. T., Brill, J. C., and Hancock, P. A. (2023). Trust in Artificial Intelligence: Meta-Analytic Findings. *Human Factors 65*: 337–359.

Kerebel, A., Cassidy, R., Jordan, P., and Holden, N. M. (2013). Farmer perception of suitable conditions for slurry application compared with decision support system recommendations. *Agricultural Systems 120*: 49–60.

Khanna, M., Atallah, S. S., Heckelei, T., Wu, L., and Storm, H. (2024). *Economics of the Adoption of Artificial Intelligence–Based Digital Technologies in Agriculture*.

Kiraly, G., Vago, S., Bull, E., Cruyssen, L. van der, Arbour, T., Spanoghe, P., and van DIJK, L. (2023, April 10). *Information behaviour of farmers, foresters, and advisors in the context of digitalisation in the EU*. Studies.Hu. https://studies.hu/information-behaviour-of-farmers-foresters-and-advisors-in-the-context-of-digitalisation-in-the-eu/ , last accessed February 26, 2024.

Kuehne, G., Nettle, R., Llewellyn, R., and Osmond, G. (2020). *Key social processes sustaining the farmer/advisor relationship*.

Lavoie, A., and Wardropper, C. B. (2021). Engagement with conservation tillage shaped by “good farmer” identity. *Agriculture and Human Values 38*: 975–985.

Lázaro, E., Makowski, D., and Vicent, A. (2021). Decision support systems halve fungicide use compared to calendar-based strategies without increasing disease risk. *Communications Earth & Environment 2*: 1–10.

Li, Z., Rau, P.-L. P., and Huang, D. (2020). Who should provide clothing recommendation services. *Journal of information technology research 13*: 113–125.

Liu, P., Du, Y., and Xu, Z. (2019). Machines versus humans: People’s biased responses to traffic accidents involving self-driving vehicles. *Accident; Analysis and Prevention 125*: 232–240.

Longoni, C., Bonezzi, A., and Morewedge, C. K. (2019). Resistance to Medical Artificial Intelligence. *The Journal of Consumer Research 46*: 629–650.

Lourenço, C. J. S., Dellaert, B. G. C., and Donkers, B. (2020). Whose algorithm says so: The relationships between type of firm, perceptions of trust and expertise, and the acceptance of financial robo-advice. *Journal of Interactive Marketing 49*: 107–124.

Macé, K., Morlon, P., Munier-Jolain, N., and Quéré, L. (2007). Time scales as a factor in decision-making by French farmers on weed management in annual crops. *Agricultural Systems 93*: 115–142.

Mahmud, H., Islam, A. K. M. N., Ahmed, S. I., and Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change 175*: 121390.

Marr, E. J., and Howley, P. (2019). The accidental environmentalists: Factors affecting farmers’ adoption of pro-environmental activities in England and Ontario. *Journal of Rural Studies 68*: 100–111.

Massfeller, A., and Storm, H. (2024). Field observation and verbal exchange as different peer effects in farmers’ technology adoption decisions. *Agricultural Economics n/a*.

McCown, R. L. (2002). Changing systems for supporting farmers’ decisions: problems, paradigms, and prospects. *Agricultural Systems 74*: 179–220.

McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and*.

McMahon, T. A., Halstead, N. T., Johnson, S., Raffel, T. R., Romansic, J. M., Crumrine, P. W., and Rohr, J. R. (2012). Fungicide-induced declines of freshwater biodiversity modify ecosystem functions and services. *Ecology Letters 15*: 714–722.

McRoberts, N., Hall, C., Madden, L. V., and Hughes, G. (2011). Perceptions of disease risk: from social construction of subjective judgments to rational decision making. *Phytopathology 101*: 654–665.

Michels, M., Bonke, V., and Musshoff, O. (2020). Understanding the adoption of smartphone apps in crop protection. *Precision Agriculture 21*: 1209–1226.

Möhring, N., and Finger, R. (2017). Pesticide use: application behavior, patterns and their determinants. *12th Conference of the European Society for Ecological Economics (ESEE 2017)* : 357–359.

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of Agricultural Science 144*: 31–43.

Önkal, D., Goodwin, P., Thomson, M., Gönül, S., and Pollock, A. (2009). The relative influence of advice from human experts and statistical methods on forecast adjustments. *Journal of Behavioral Decision Making 22*: 390–409.

Otter, V., and Deutsch, M. (2023). Did policy lose sight of the wood for the trees? An UTAUT-based partial least squares estimation of farmers acceptance of innovative sustainable land use systems. *Land Use Policy 126*: 106467.

Rohleder, B., and Meinel, T. (2024). *So digital ist die Landwirtschaft*.

Rojo-Gimeno, C., van der Voort, M., Niemi, J. K., Lauwers, L., Kristensen, A. R., and Wauters, E. (2019). Assessment of the value of information of precision livestock farming: A conceptual framework. *NJAS - Wageningen Journal of Life Sciences 90–91*: 100311.

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., and Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural Systems 149*: 165–174.

Rossi, V., Sperandio, G., Caffi, T., Simonetto, A., and Gilioli, G. (2019). Critical Success Factors for the Adoption of Decision Tools in IPM. *Agronomy 9*: 710.

Rübcke von Veltheim, F., Theuvsen, L., and Heise, H. (2022). German farmers' intention to use autonomous field robots: a PLS-analysis. *Precision Agriculture 23*: 670–697.

Schneider, K., Barreiro-Hurle, J., and Rodriguez-Cerezo, E. (2023). Pesticide reduction amidst food and feed security concerns in Europe. *Nature Food 4*: 746–750.

Sharma, A., Kumar, V., Shahzad, B., Tanveer, M., Sidhu, G. P. S., Handa, N., Kohli, S. K., Yadav, P., Bali, A. S., Parihar, R. D., Dar, O. I., Singh, K., Jasrotia, S., Bakshi, P., Ramakrishnan, M., Kumar, S., Bhardwaj, R., and Thukral, A. K. (2019). Worldwide pesticide usage and its impacts on ecosystem. *SN Applied Sciences 1*.

Shtienberg, D. (2013). Will Decision-Support Systems Be Widely Used for the Management of Plant Diseases? *Annual Review of Phytopathology 51*: 1–16.

Skaalsveen, K., Ingram, J., and Urquhart, J. (2020). The role of farmers' social networks in the implementation of no-till farming practices. *Agricultural Systems 181*: 102824.

Skevas, T., Stefanou, S. E., and Oude Lansink, A. (2014). Pesticide use, environmental spillovers and efficiency: A DEA risk-adjusted efficiency approach applied to Dutch arable farming. *European Journal of Operational Research 237*: 658–664.

Smith, R., and Van den Bosch, R. (1967). Integrated control. *Pest Control: Biological, Physical and Selected Chemical Methods* : 295–340.

Storm, H., Heckelei, T., and Baylis, K. (2024). Probabilistic programming for embedding theory and quantifying uncertainty in econometric analysis. *European Review of Agricultural Economics* : jbae016.

Stranieri, S., Varacca, A., Casati, M., Capri, E., and Soregaroli, C. (2022). Adopting environmentally-friendly certifications: transaction cost and capabilities perspectives within the Italian wine supply chain. *Supply Chain Management: An International Journal 27*: 33–48.

Sutherland, L.-A. (2013). Can organic farmers be 'good farmers'? Adding the 'taste of necessity' to the conventionalization debate. *Agriculture and Human Values 30*: 429–441.

Sutherland, L.-A., and Darnhofer, I. (2012). Of organic farmers and ‘good farmers’: Changing habitus in rural England. *Journal of Rural Studies 28*: 232–240.

Swinney. (1999). *Consideration of the social context of auditors’ reliance on expert system output during evaluation of loan loss reserves*.

Varacca, A. (2024). Latently mediating: A Bayesian take on causal mediation analysis with structured survey data. *Multivariate Behavioral Research* : 1–23.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *The Mississippi Quarterly 27*: 425–478.

Wang, Y.-Y., and Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments 30*: 619–634.

Weersink, A., and Fulton, M. (2020). Limits to Profit Maximization as a Guide to Behavior Change. *Applied Economic Perspectives and Policy 42*: 67–79.

Westerink, J., Pleijte, M., Schrijver, R., van Dam, R., de Krom, M., and de Boer, T. (2021). Can a ‘good farmer’ be nature-inclusive? Shifting cultural norms in farming in The Netherlands. *Journal of Rural Studies 88*: 60–70.

Workman, M. (2005). Expert decision support system use, disuse, and misuse: a study using the theory of planned behavior. *Computers in Human Behavior 21*: 211–231.