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Farmers' Behavior and Policy Design in the Era of Smart Farming Technology

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Kurzfassung

Der Agrarsektor steht vor der doppelten Herausforderung, Ernährungssicherheit zu gewährleisten und gleichzeitig die Umwelt zu schützen. Bevölkerungswachstum, Klimawandel und Umweltbelastungen verschärfen diese Herausforderung. Ein vielversprechender Lösungsansatz ist der Wandel hin zur nachhaltigen Intensivierung – das bedeutet: gesteigerte Produktion bei verminderten Umweltauswirkungen. Intelligente Agrartechnologien (Smart Farming Technologies, SFT), insbesondere solche auf Basis künstlicher Intelligenz (KI), bieten großes Potenzial zur Unterstützung dieses Wandels durch autonome Datenerfassung sowie zeit- und standortgenaue Bewirtschaftung. Allerdings verwenden Landwirt*innen SFT bislang nur in begrenztem Ausmaß und die Gründe dafür sind noch nicht vollständig geklärt. Politisch verfolgt die EU-Agrarpolitik das Ziel, die Digitalisierung und nachhaltige Praktiken durch Anreize zu fördern, wurde aber vielfach als ineffizient kritisiert. SFT könnten hier durch ergebnisorientierte Ansätze unterstützen – jedoch fehlt es an Forschung zur Integration ihrer Potenziale in der Politikgestaltung.

Die vorliegende Dissertation adressiert diese Wissenslücken durch empirische Studien zur Interaktion von Landwirt*innen, SFT und Agrarpolitik in Europa. Ziel ist es zu verstehen, welche Faktoren das Verhalten von Landwirt*innen beeinflussen, wie SFT die Politikgestaltung verändern könnten und welche politischen Maßnahmen ergriffen werden müssten, um das Potenzial digitaler Technologien für eine nachhaltige Intensivierung zu nutzen. Kapitel 2 analysiert, wie sogenannte „Peer-Effekte“ – insbesondere verbaler Austausch und Wahrnehmung von Feldern anderer Landwirt*innen – die Technologienutzungsentscheidung beeinflussen. Basierend auf Umfragedaten von 313 Landwirt*innen in Deutschland und einem innovativen, räumlich-expliziten Erhebungsinstrument zeigt eine Double-Selection-LASSO-Analyse, dass beide Peer-Mechanismen positiv mit der Nutzungsentscheidung zusammenhängen und sich gegenseitig verstärken. Die Wahrscheinlichkeit der Technologienutzung ist am höchsten für Landwirt*innen, die viele Felder in räumlicher Nähe wahrnehmen, auf denen die neue Technologie genutzt wird und die mit vielen anderen Nutzer*innen sprechen. In Kapitel 3 wird die Zahlungsbereitschaft von 250 Landwirt*innen für KI-basierte Entscheidungshilfen anhand eines Online-Experiments untersucht. Die Ergebnisse eines bayesianischen Modells zeigen eine klare „Algorithmus-Aversion“: Landwirt*innen bevorzugen menschliche Empfehlungen gegenüber KI, selbst bei überlegener Leistung der KI. Das Kapitel führt das Konzept der KI-Angst als zentralen Erklärungsfaktor für zukünftige Verhaltensmodelle ein. Kapitel 4 verlagert den Fokus auf die Politikgestaltung: Mit Hilfe eines Simulationsmodells wird untersucht, wie intelligente Unkrautroboter die Ausgestaltung von Zahlungen für Ökosystemleistungen beeinflussen können. Die Fähigkeiten der Roboter (selektive Bekämpfung und autonome Datenerfassung) erhöhen die Effizienz sowohl aktions- als auch ergebnisbasierter Politikansätze. Dies verschiebt die bisherigen Grenzen der Politikdesignoptionen.

Diese Arbeit leistet aus theoretischer, empirischer und methodischer Perspektive einen Beitrag zum Verständnis des Technologieverhaltens von Landwirt*innen und zur Rolle von SFT in der Agrarpolitik. Sie zeigt auf, wie SFT effizient zur Politikgestaltung genutzt werden können. Soziale Lernprozess können helfen, der KI-Skepsis von Landwirt*innen entgegenzutreten. Eine erfolgreiche Technologie-Einführung erfordert jedoch Unterstützung: Entscheidungsträger in Politik, Beratung und Technologieentwicklung sollten gemeinsam die Potentiale kommunizieren, wahrgenommene Hürden abbauen und die Fähigkeiten von SFT zur Unterstützung nachhaltiger Intensivierung gezielt einsetzen.

Abstract

The agricultural sector faces a dual challenge: ensuring food security while simultaneously protecting the environment. Population growth, climate change, and environmental degradation exacerbate this challenge. A promising pathway to address it is a shift towards sustainable intensification—that is, achieving higher productivity while reducing negative environmental impact. Smart farming technologies (SFT), particularly those based on artificial intelligence (AI), offer substantial potential to support this transition by enabling autonomous monitoring and site- and time-specific management. Nevertheless, the adoption of these technologies by farmers remains limited, and substantial knowledge gaps persist regarding farmers' behavior towards SFT. At the policy level, the European Union's Common Agricultural Policy aims to promote digitalization and sustainable practices through financial incentives, but such programs have often been criticized as inefficient and ecologically ineffective. SFT could support more results-oriented policy instruments; however, research is lacking on how their capabilities could concretely influence policy design.

This dissertation addresses these research gaps through empirical studies that examine the interaction between farmers, SFT, and agricultural policy in Europe. The aim is to deepen the understanding of the factors that influence farmer behavior, how SFT may reshape policy-making, and how optimal policies can leverage the potential of SFT to support sustainable intensification in the agricultural sector. Chapter 2 analyzes how "peer effects"—specifically verbal exchange and field observation among farmers—influence farmers' technology adoption decisions. Using survey data from 313 sugar beet farmers in Germany and a novel, spatially explicit survey tool, we employ a double-selection LASSO approach. The results show that both forms of peer effects significantly affect adoption and mutually reinforce one another. The likelihood of adoption is highest for farmers that observe many fields in close spatial proximity and verbally exchange with many adopters. Chapter 3 investigates farmers' preference for AI-based decision-support tools. Based on an online survey and an embedded economic experiment involving 250 German farmers, the chapter uses a novel Bayesian probabilistic programming approach to quantify the willingness to pay. The findings reveal clear "algorithm aversion": farmers prefer recommendations from human advisors over those generated by AI—even when the AI outperforms the human. The chapter introduces the concept of AI anxiety as a key behavioral factor and proposes its integration in future technology adoption models. Chapter 4 shifts the focus to agricultural policy by examining how smart weeding robots could affect the design of payments for ecosystem services. Using a simulation model, we explore how the robots' capabilities—selective weeding and autonomous monitoring—could enhance the efficiency of both action-based and results-based payments. We find that improved monitoring supports the efficiency of results-based schemes, while selective weeding can improve action-based approaches. Overall, the efficiency of both payment types increases compared to when no robot is used, which shifts the frontier of current policy design options.

In sum, this dissertation contributes theoretically, empirically, and methodologically to a better understanding of farmers' behavior towards SFT and identifies how SFT could change agricultural policy design. The findings of this dissertation show that using SFT for sustainable intensification has the potential to make agricultural policies more effective. However, technology introduction alone is not sufficient—appropriate guidance is essential to ensure proper use. Social learning can help to address farmers' algorithm aversion. Policy makers, advisory services and technology developers should work together to facilitate large-scale adoption by clearly communicating benefits and reducing (perceived) efforts for farmers.

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Abbreviations

2SLS	Two Stage Least Squares
AA	Algorithm Aversion
ABS	Action-Based Scheme
AI	Artificial Intelligence
AIA	AI-Anxiety
CAP	Common Agricultural Policy
DAG	Directed Acyclic Graph
DGP	Data Generating Process
DST	Decision Support Tool
EU	European Union
FAIR	Findable, Accessible, Interoperable, Reusable Data
ha	Hectare
HPDI	Highest Posterior Density Interval
IFZ	Institut für Zuckerrübenforschung
IM	Intention Model
LASSO	Least Absolute Shrinkage and Selection Operator
LM	Lasso Model
mAP	Mean Average Precision
MCMC	Marcov Chain Monte Carlo
ODD	Overview, Design concepts, Details
OSF	Open Science Framework
PES	Payments for Ecosystem Services
PP	Probabilistic Programming
RBS	Results-Based Scheme
SFT	Smart Farming Technology
t	Tons
UAA	Utilized Agricultural Area
UAV	Unmanned Aerial Vehicle
UK	United Kingdom
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology
WTP	Willingness-To-Pay

Chapter 1
Introduction

1.1 Background and Problem Statement

Every day, nearly 9 million farmers in the European Union (EU) decide which crops to grow, how much plant protection to apply, or whether to invest in a new technology. Although farmers constitute only 4% of the EU population, their decisions shape roughly 40% of the EU's land area (Eurostat, 2025a, 2025b). This remarkable influence comes with dual responsibilities: ensuring food safety while protecting the environment (FAO, 2024). Hence understanding farmers' decision-making is paramount to address the multiple pressures affecting the agri-food sector: Global food demand is increasing while climate change and external shocks threaten agricultural production and the resilience of the agri-food system (Borrelli et al., 2020; Gouel & Guimbard, 2019; Ortiz-Bobea et al., 2021). At the same time, agricultural production contributes to habitat loss (Kehoe et al., 2017; Pendrill et al., 2022), nutrient cycle disruption (Tang et al., 2021), and substantial global greenhouse gas emissions (Tubiello et al., 2022), thus leading to a transgression of several planetary boundaries (Campbell et al., 2017; IPCC, 2022; Richardson et al., 2023). Addressing these challenges calls for a shift towards resilient and increasing food production while reducing environmental damage. This approach, known as *sustainable intensification*, holds great potential (Caiado et al., 2017; Lindblom et al., 2017; Weltin & Hüttel, 2023); but hinges on farmers' adjusting their farm-level decisions accordingly.

Digitalization of the agri-food sector – often termed the 4th agricultural revolution – is seen as key to reaching sustainable intensification (Finger, 2023; Khanna, 2025; Walter et al., 2017). Smart farming technologies (SFTs) leverage advanced information and communication tools to process vast amounts of unstructured data (Finger, 2023; Klerkx & Rose, 2020; David Christian Rose & Chilvers, 2018; Storm, Seidel, et al., 2024; Wolfert et al., 2017), by increasingly relying on artificial intelligence (AI) (Khanna et al., 2024). This enables SFTs to learn from the outcomes of previous tasks and allows to enhance resource use efficiency, substitute harmful inputs and enables a redesign of the agri-food system (Finger, Benni, et al., 2019; Finger, 2023; Khanna et al., 2024; Storm, Seidel, et al., 2024; Wolfert et al., 2017). This is mainly possible through two novel abilities: Continuous and autonomous monitoring, as well as site- and time-specific treatments. Site- and time specific treatments of e.g. crops can be enabled by combining data from various sources in real time at fine spatial resolution. Based on these two abilities, SFTs can provide precise predictions and recommendations for farmers leading to more sustainable, resilient and efficient farming (Finger, 2023; Khanna et al., 2024). Yet, for SFTs to unfold their full potential, farmers need to adopt and use the technology in the intended way.

However, gaps remain in fully understanding the adoption process of SFT. As suggested by the induced innovation hypothesis, farmers adopt new technologies when they perceive benefits (Acemoglu, 2002; Hicks & Simiand, 1932). For example, farmers who perceive positive environmental benefits from pesticide-free weeding tend to adopt this type of production (Finger & Möhring, 2022). However, technologies are often not fully understood by farmers in advance, hence adoption[1] decisions are shaped by uncertainty and the (in)availability of information. Information – acquired through learning-by-doing or by learning from others (social learning) – plays a crucial role in whether and how farmers assess the suitability, profitability and, ultimately, the benefits of a given technology (Chavas & Nauges, 2020). The importance of knowledge and (social) learning as prerequisite for technology adoption and diffusion is acknowledged in several theories (e.g. Rogers, 2003) and an extensive body of literature has studied this topic empirically over the past decades (Albizua et al., 2021;

[1] While the term “adoption” can be defined in various ways, in this chapter we use this word for all types of adoption including full, partial, temporal, binary, continuous, and opportunistic adoption by farmers (Pannell, 2008).

Bandiera & Rasul, 2006; Besley & Case, 1993; Blasch et al., 2020; Conley & Udry, 2010; Foster & Rosenzweig, 1995, 2010; McCann et al., 2015; Mekonnen et al., 2022; Noy & Jabbour, 2020; Sampson & Perry, 2019; Skaalsveen et al., 2020; Šūmane et al., 2018). Yet the technology adoption process is characterized by much heterogeneity: if and to what extent a technology is perceived as beneficial depends on the individuum, the technology attributes and the external production conditions (Feder et al., 1985; Pannell & Claassen, 2020; Schulz & Börner, 2022). Similarly, if and to what extent information is obtained either through learning-by-doing or social learning depends on various factors. These range from the individuum and the external production conditions over the social network to whether the characteristics that determine the outcome of a new technology are easily observable (Chavas & Nauges, 2020; McCann et al., 2015; Rogers, 2003; Tjernström, 2017). This complex combination of personal characteristics, behavioral factors, technology attributes and external conditions complicate a systematic comprehension of the full technology adoption process (Feisthauer et al., 2024; Shang et al., 2021; Streletskaya et al., 2020).

To date, no study has examined the role of observability and AI as specific technology attributes that can affect the adoption and usage of new technology. Shang et al. (2021) highlight that observability of a technology could serve as an information source and driver of social learning in farmers' technology adoption decisions, but that much uncertainty persists regarding this technology attribute. Further, despite the growing relevance of AI in agricultural management and its potential to enhance efficiency, AI as a technology attribute has received limited attention in research on farmers' decision-making (Mahmud et al., 2022). Empirical evidence on farmers' perceptions and acceptance of AI in agriculture remains scarce (see De la Peña & Granados, 2024; and Orn et al., 2020 for two examples). Currently, there is little knowledge on how farmers perceive the potential benefits of AI and how individual personality traits shape their responses to it. These gaps hinder a comprehensive understanding of farmers' behavior toward SFT and limit the development of effective strategies to support the adoption of AI-based technologies.

Overall, as pointed out by Finger (2023), this lack of understanding leads to a mismatch between the potential of novel technologies and farmers' actual adoption: On the one hand, those technologies with the highest potential to reduce resource usage might not be the most profitable to farmers and are therefore not adopted. On the other hand, farmers might not use even profitable technologies: first, because farmers' adoption decisions are not only driven by profit-maximization (Streletskaya et al., 2020) and second, because farmers might not know about the potential benefits of the technology (Chavas & Nauges, 2020).

Consequently, upscaling technology adoption and promoting a development towards sustainable intensification require the development and implementation of policy measures. Digitalization and environmental sustainability are central to the EU's Common Agricultural Policy (CAP) (European Commission, 2020b), reinforced by approaches such as the *Farm to Fork Strategy* and the *Biodiversity Strategy* (European Commission, 2020a, 2021a). Currently, voluntary payments for ecosystem services (PES) have become key instruments to support the transition by compensating farmers for providing public goods beyond regulatory requirements (Wuepper et al., 2024; Wunder et al., 2020). Yet, the CAP and PES have long been criticized as inefficient and costly (Mennig, 2024). Farmers receive public money for specific actions, but the environmental, public outcomes remain limited or absent (Brown et al., 2021; M. Meyer et al., 2025; Pe'er et al., 2017). Further, recent protests reflect farmers' reluctance to participate in such schemes (Finger et al., 2019), likely due to the intangible, uncertain, and hard-to-measure benefits at the farm level (Pannell & Claassen, 2020). One promising approach to address these challenges is to shift from action-based (ABS) to results-based schemes (RBS)[2], which reward farmers for achieving defined outcomes rather than performing prescribed actions. This may increase efficiency and improve acceptance, as farmers retain flexibility in how to reach the targets (Burton & Schwarz, 2013). However, RBS face two major barriers: the lack of reliable indicators

[2] Various terms are used in this context, including "outcome-oriented," "outcome-based," and "output-oriented" (Schilizzi et al., 2011), "payment-by-results" (Schroeder et al., 2013), "result-oriented" (Burton & Schwarz, 2013), and "results-based" (Herzon et al., 2018; Russi et al., 2016). We use the term "results-based schemes" and RBS throughout.

to measure success, and farmers' fear of losing payments if results are not met despite effort (Chaplin et al., 2021). Recent research suggests that digitalization can help overcome these barriers (Ehlers et al., 2022, 2021; Finger, 2023; OECD, 2019; Walter et al., 2017). Here, most research focuses on SFTs' monitoring functions, for example the use of acoustic sensors (Markova-Nenova et al., 2023), drones (Basavegowda et al., 2025), and digital fencing (Wätzold et al., 2024) to facilitate the implementation of RBS. But little attention is paid to SFTs' potential for time- and site-specific interventions, that help reduce trade-offs between production and environmental goals, e.g. between crop yield and weed biodiversity (Zingsheim & Döring, 2024). This paucity impedes a clear understanding of how SFTs might imply changes in agricultural policy design.

So far, two main research gaps evolve: First, farmers' behavior towards SFTs is not fully understood and second, evidence is lacking on how SFTs might change agricultural policy design. In consequence, it remains unclear what optimal – i.e. effective and behaviorally aligned – policies should look like, that leverage SFTs' potential for sustainable intensification while avoiding unintended consequences (Daum, 2021). Ultimately, this knowledge gap can impose costs on farmers, taxpayers, and the environment (Finger, Benni, et al., 2019). To fill this third gap, we aim to identify what optimal policy design should look like in the era of SFT.

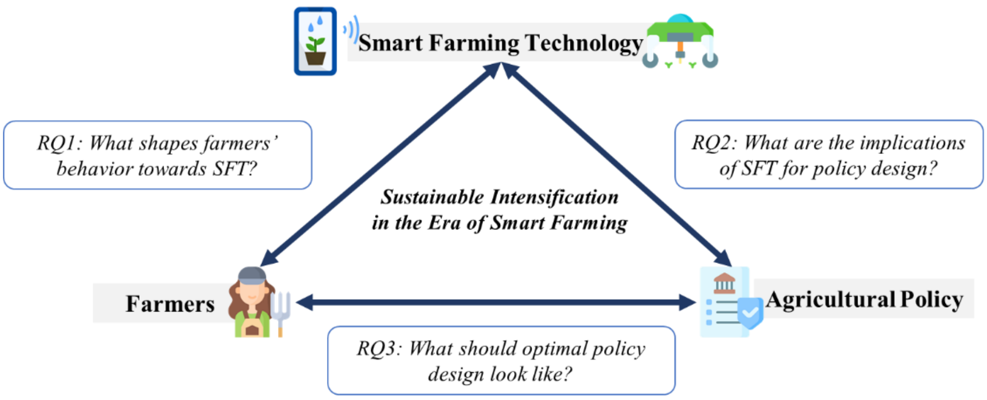

Figure 1.1: Overview of the topical background and resulting research questions, own illustration

In summary, to understand how the agricultural sector can develop towards sustainable intensification in the era of smart farming, three key perspectives need to be considered, as illustrated in Figure 1.1: i) farmers as decision-makers at the farm level, ii) SFTs and their novel attributes, and iii) agricultural policy. As outlined above, these perspectives are interlinked, yet little is known about how they interact: First, farmers' behavior towards SFTs is not fully understood. Second, the impact of SFTs on the design of policy instruments requires further investigation. Third, in consequence, there is insufficient knowledge on how policy instruments should be designed to leverage the potential of SFTs to effectively guide farmers' adoption and use of SFTs in support of sustainable intensification. This thesis contributes to closing these research gaps.

1.2 Aim and Research Questions

The aim of this thesis is to deepen the understanding of the interaction between farmers, SFTs and agricultural policy design, to inform decision-makers on how to leverage the potential of SFTs to support sustainable intensification of the agricultural sector. To this end, this thesis seeks to answer the following research questions (RQ) by using empirical methods and quantitative data:

RQ 1: What shapes farmers' behavior towards SFTs?

RQ 2: What are the implications of SFTs for agricultural policy design?

RQ 3: What should optimal policy design look like to leverage the potential of SFTs for sustainable intensification?

Figure 1.2 illustrates the structure of this thesis. The chapters vary regarding the stage of the focal technology, the data used and the methodology. Chapters 2 and 3 contribute to answering the first research question by focusing on behavioral factors explaining farmers technology adoption decisions. In Chapter 2, we rely on data from an online survey with German sugar beet farmers that we analyze using machine learning. In Chapter 3, the data stems from an online experiment and we apply a novel Bayesian probabilistic programming approach for the analysis. Chapter 4 addresses

Research Question 2 by employing a simulation model based on secondary data to study the effect of SFT on PES efficiency. While Chapter 2 focuses on the current adoption status of an existing technology (mechanical weeding), Chapters 3 and 4 look at technologies that are not yet widely used, namely AI-based decision support tools (AI-DST), and smart weeding robots. Together, the synthesis of all three Chapters allows to answer the third research question by deriving recommendations for various decision-makers.

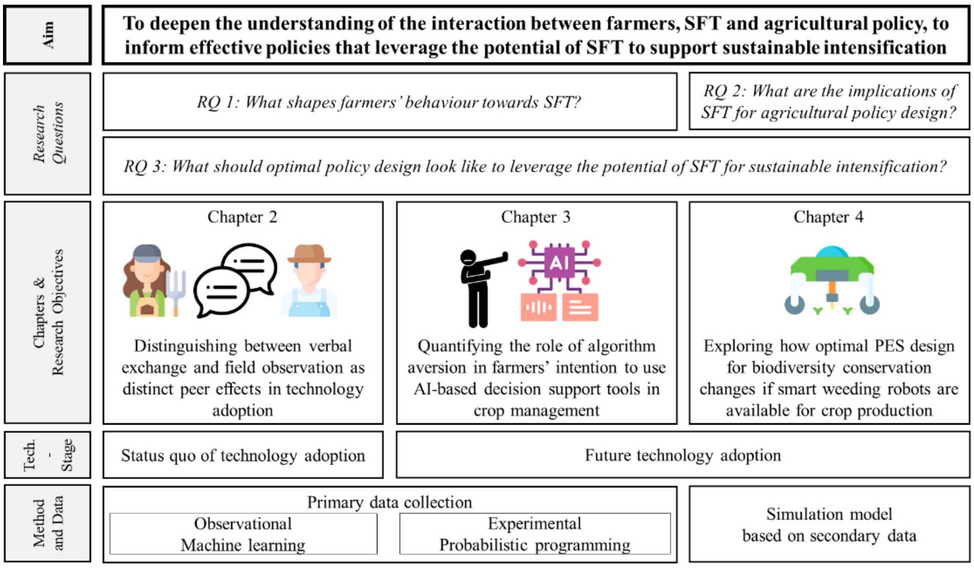

Figure 1.2: Structure of the thesis, own illustration

To enable transparency and replicability of all studies, we follow the principles of open science and findable, accessible, interoperable, and reusable (FAIR) data procedures (Storm, Heckelei, et al., 2024). We share code and (where possible) data. The two surveys for Chapters 2 and 3 were pre-registered on the Open Science Framework (OSF) and we obtained ethical clearance before data collection.

In all three chapters we focus on crop production in Europe, which is characterized by high intensity (Gianessi & Williams, 2011). Natural and climatic conditions as well as the use of various inputs like fertilizer and pesticides have provided Europe with the highest crop yields worldwide, thereby contributing to global food security and safety (FAO, 2025a; Gianessi & Williams, 2011; Oerke, 2006). Germany, the country Chapters 2 and 3 focus on, is among the ten countries with the highest yields worldwide in wheat, barley and sugar beets (FAO, 2025a). At the same time, it has the third highest use of pesticides (in tons applied) within the EU (FAO, 2025b), which comes with unintended negative consequences for human health (Hossain et al., 2017) and the environment, especially biodiversity (Fritsch et al., 2024; Geiger et al., 2010).

The remainder of this introductory chapter is structured as follows: Section 1.3, presents the contributions of each chapter to answer the research questions and to reach the overall research aim, by providing more detailed insights into the different methods used and the results obtained. Section 1.4. answers the third research question by synthesizing the findings of the three chapters to derive policy recommendations. Section 1.5 concludes with a reflection on limitations and an outline of future research avenues.

1.3 Contributions

In the following, detailed information on each chapter is provided by presenting the concrete research gap, the theoretical, methodological and empirical contributions and how the chapter addresses the research questions.

1.3.1 *Field observation and verbal exchange as different peer effects in farmers' technology adoption decisions*[3]

Peer influence plays a key role in farmers' decisions to adopt new technologies (Shang et al., 2021). While previous research has explored different types of peer effects, such as verbal communication (Albizua et al., 2021) and field observation (Mekonnen et al., 2022), the mechanisms behind these effects are not well understood (Bramoullé et al., 2020). To date, no study has clearly differentiated between peer effects based on verbal exchange versus those arising from field observation. We aim to fill this gap by answering the following research questions:

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[3] This chapter is published as Massfeller, A., and Storm, H. (2024). “Field observation and verbal exchange as different peer effects in farmers’ technology adoption decisions.” Agricultural Economics 55 (5), 739-757. https://doi.org/10.1111/agec.12847

1. How do (verbal) information exchange and field observation relate to adoption of technology?
2. Do the two types complement each other in explaining the technology adoption decision?
3. How do the two types relate to each other within the relevant socio-spatial network?

Understanding these underlying mechanisms is crucial for improving advisory services and policy interventions (Bartkowski & Bartke, 2018; Bramoullé et al., 2020). The study focuses on the adoption of mechanical weeding among 313 sugar beet farmers in Germany, using survey data from early 2022. Sugar beet farming in Germany heavily depends on herbicides (Nause et al., 2021). With growing environmental concerns, alternative methods like mechanical weeding are becoming more important as a potential solution (BLE, 2018; Warnecke-Busch et al., 2020). We design a novel custom-built survey tool that enables us to gather spatially explicit data: participants are asked to identify their fields and the fields of other farmers where mechanical weeding has been observed on an interactive map. Additionally, farmers indicate whether they used mechanical weeding techniques and how many other adopters they know.

The study is embedded in Rogers' Theory of Diffusion of Innovation (Rogers, 2003), which explicitly considers the observability of a new technology as an important attribute explaining the adoption decision. From an econometric point of view, identifying peer effects is challenging, as individual behaviors may be influenced by various factors stemming from endogenous, exogenous, and correlated effects – a challenge known as reflection problem (Manski, 1993). We are interested in the endogenous effects, that is, the correlation between the farmer's peers' and their own adoption decision through field observation and/or knowing adopters. To mitigate biases from correlated effects and, to a lesser extent, exogenous effects, we include farm- and county-level control variables in our analysis. This includes the distance to demonstration farms or the affiliations of farmers with specific sugar factories, as well as county-level farm demographics.

To handle the large number of control variables in combination with the relatively small sample size of 313, we employ a Least Absolute Shrinkage and Selection Operator (LASSO) (Finch & Hernandez Finch, 2016) with a double-selection approach (Belloni & Chernozhukov, 2014; Belloni et al., 2014). LASSO is a state-of-the-art machine learning approach that allows to avoid high variance in parameter estimates (Storm et al., 2019). This method helps to identify the most relevant explanatory variables that should be included in the model and thereby improves model accuracy. The double-selection approach allows to address the danger of omitted variable bias caused by control variables that are correlated with both the outcome (i.e. adoption) and the variables of interest (i.e. observing fields and knowing adopters). Assuming no unobserved confounders, this approach ensures that relevant controls are included even if their effects are indirectly captured by our variables of interest.

Our findings suggest that both verbal exchange and field observation are positively related to technology adoption, whereby verbal exchange seems to play a slightly more pronounced role. Both verbal information exchange and field observation play a key role in facilitating adoption, consistent with previous research (Mekonnen et al., 2022; Sampson & Perry, 2019). While highly correlated, the two peer effects complement each other in explaining adoption decisions. In a socio-spatial network with many known adopters and many observed fields in close spatial distance, the likelihood of adoption is highest and verbal exchange and field observation reinforce one another. This study offers a foundation for future research into the causal relationships behind peer effects and introduces a new survey tool for capturing spatially explicit data on farmers' fields. Our findings suggest that advisory services should focus on establishing personal contact between adopters and non-adopters. Given the complementary relationship, field observation possibilities should always be accompanied by the option to verbally exchange. To enhance the resource efficiency of policy measures and extension services, SFTs, like weeding robots, could be offered on a trial basis to selected farmers in nearby regions.

1.3.2 *Are Farmers Algorithm-Averse? The Case of Decision Support Tools in Crop Management*[4]

Chapter 3 focuses on a technology that is not yet broadly adopted but currently under development and promising: Decision Support Tools (DST) based on Artificial Intelligence (AI). AI plays an increasingly important role in farmers' daily life and AI-based DSTs have been developed by both public and private actors, to increase productivity, improve resource use efficiency, and support adaptation to climate change (Yousaf et al., 2023). However, their success hinges on farmers' willingness to adopt. Research shows that most farmers rely more on advisory services and peer communication than on digital tools (Giulivi et al., 2023; Helps et al., 2024; Kiraly et al., 2023; Lázaro et al., 2021; Skaalsveen et al., 2020). This resistance to algorithmic recommendations – even when clearly superior to human advice – is known as algorithm aversion (Dietvorst et al., 2015). Economically, algorithm aversion can be understood as a deviation from rational behavior: individuals reject the AI-DST despite its potential for more efficient management. Understanding this behavioral deviation is crucial, as these tools offer a path toward resource-efficient farming and reduced environmental impacts while maintaining high yields. However, the phenomenon remains understudied in agricultural decision-making (Mahmud et al., 2022). Therefore, the third chapter addresses the research question:

> What role does algorithm aversion play in farmers' intention to use AI-DST?

To answer this question, we conduct an online survey with 250 German arable farmers in autumn 2024 to elicit both farmers' intention to use AI-DSTs and their Willingness-To-Pay (WTP) for different types of advice (AI vs. human). Within the survey, we employ an economic experiment to elicit farmers' algorithm aversion. We test whether and to what extent farmers prefer a human advisor over an AI-based DST, whereby we give different

[4] This chapter is currently under review at the American Journal of Agricultural Economics as Massfeller, A., Hermann, D., Leyens, A., Storm, H. (2025). "Are Farmers Algorithm-Averse? The Case of Decision Support Tools in Crop Management".

information on the performance of both options (both perform equal, or one better than the other). We further measure farmers' latent AI-anxiety on a 7-point Likert-Scale following Wang and Wang (2022).

To design the survey and analyze the data, we employ a Bayesian probabilistic programming (PP) workflow based on Storm et al.(2024) and following Gelman et al. (2020) and McElreath (2018). This approach offers several advantages, including improved transparency through a theoretically motivated data-generating process (DGP), iterative pretesting with synthetic data, and validation of code, inference, and visualization as part of the pre-registration. Statistically, it provides clear benefits in expressing and interpreting parameter uncertainty compared to frequentist methods (Storm, Heckelei, et al., 2024). To our knowledge, this represents one of the first full applications of the Bayesian workflow in experimental studies in this field (cf. Leyens et al., 2024; Stranieri et al., 2022; Varacca, 2024).

Our findings show that most farmers prefer human advisors even when the AI tool performs better. That is, algorithm aversion plays a dominant role in farmers' intention to use and their WTP for AI-DST. We calculate a performance premium, i.e., how much better the AI-DST needs to perform to be equally preferred as human advice. For most farmers in our sample, the AI-DST must outperform the human advisor by 11% to 30%. Similarly, an AI-DST with the same performance as a human would need to be 21% to 56% cheaper for most farmers to be perceived similarly valuable. Methodologically, we propose the developed PP workflow for future experimental studies.

Chapter 3 helps reaching the overall aim of this dissertation by exploring farmers' behavior towards novel, AI-based SFTs. Building on our findings that many farmers may display algorithm aversion, we propose incorporating AI-anxiety as a novel dispositional factor in behavioral research on farmers' adoption of AI technologies and thereby extending frameworks on behavioral factors such as that of Déssart et al. (2019). Further, our results underscore the need for technology developers to account for algorithm aversion when designing AI-based decision support tools. In particular, the significance of the performance premium highlights the importance of transparently communicating the value and reliability of

AI tools to end-users. Given farmers' strong preference for human advice, agricultural advisory services must carefully assess which services are best suited for AI and where human expertise remains indispensable.

1.3.3 *Action- or results-based payments for ecosystem services in the era of smart weeding robots?*[5]

Payments for ecosystem services (PES) are commonly used to mitigate the negative impacts of agriculture on biodiversity (Wunder et al., 2020, 2008). PES schemes can be either action-based (ABS), where farmers are rewarded for specific actions, or results-based (RBS), where farmers receive payments based on predefined biodiversity indicators. To date, most existing RBS focus on biodiversity in grasslands or wildlife conservation. Only few examples are found in arable farming (Elmiger et al., 2023; Hagemann et al., 2025), but engagement towards environmental protection is needed in these intensive systems. Research suggests that digitalization and new technologies will help to overcome current limitations of RBS (Besson et al., 2022; Ehlers et al., 2021; Finger, 2023), including the need for measurable and low-cost indicators, and a reduction of the financial risks for farmers if targets are not met (Burton & Schwarz, 2013; Zabel & Roe, 2009). However, these assumptions have only been scarcely explored empirically. Further, to date most research in this area focuses on SFTs' monitoring capacity (cf. Basavegowda et al., 2025; Markova-Nenova et al., 2023; Wätzold et al., 2024), while other novel abilities like time- and site-specific treatments are neglected.

Therefore, in Chapter 4, we examine how the availability of smart weeding robots could influence PES in the case of biodiversity conservation in crop production. Specifically, we focus on the robot's abilities to autonomously monitor plants and selectively remove weeds using non-chemical methods or variable-rate herbicides. We focus on weeding robots as they have the potential to reduce the trade-off between crop production and environmental

[5] This chapter is published as Massfeller, A., Zingsheim, M., Ahmadi, A., Martinsson, E., Storm, H. (2025). Action- or results-based payments for ecosystem services in the era of smart weeding robots? Biological Conservation 302, 110998. https://doi.org/10.1016/j.biocon.2025.110998

degradation, i.e. to enhance biodiversity conservation while maintaining high yields (Bawden et al., 2017; Fennimore & Cutulle, 2019; Slaughter et al., 2008; Storm, Seidel, et al., 2024; Zingsheim & Döring, 2024). Concretely, we aim to answer the following research questions:

1. How do weeding robots affect optimal PES scheme designs?
2. What challenges and options might arise for future scheme designs once weeding robots are used?

To this end, we apply a simulation model based on Gibbons et al. (2011) in which we illustrate how weeding robots' abilities to selectively remove weeds and to monitor plants could affect PES design and efficiency. Taking an interdisciplinary perspective combining insights from tech-development, agro-ecology and agricultural economics, we first diagnose changes in weed management arising through the availability of weeding robots. Second, we identify the relevant parameters in the model to reflect these identified changes and extend the set-up of the model where necessary. As a third step, we define plausible directions and ranges of how each parameter might be affected by weeding robots based on empirical evidence where possible. Fourth, we use those ranges to simulate and compare the relative preferability of RBS and ABS when weeding robots are available.

We find that the efficiency, that is biodiversity gain per agency costs, of ABS and RBS may be improved by the abilities of smart weeding robots. Reliable monitoring can reduce costs for RBS and mitigate the risk for farmers that results are achieved but not detected. At the same time, the robot's ability to selectively remove weeds allows for more biodiversity-sensitive actions. That means the actions executed by a robot come with a clear benefit for biodiversity. This contrasts previous actions farmers carried out as part of ABS which not necessarily lead to the desired biodiversity gain. As a result, the relative efficiency of ABS compared to RBS increases. Overall, with increasing weeding sensitivity and monitoring capacity, the difference in efficiency between ABS and RBS vanishes. In both cases, we observe the status quo of biodiversity before scheme participation to play an important role for scheme efficiency.

Chapter 4 contributes to the overall research aim of this thesis by providing insights on how a smart weeding robot as a novel SFT might induce changes in agricultural policy design. Specifically, we identify how the abilities of smart weeding robots could help to increase the efficiency of PES. This enables us to inform decision-makers on how to leverage the potential of SFTs to support a development towards sustainable intensification. Given the importance of robot's ability to perform biodiversity-sensitive actions, we conclude that technology developers need to design robots that are not only reliably removing weeds, but that can i) identify various individual plants in various growth stages and ii) distinguish between crops and non-crops and iii) execute weeding based on different rationales like competitiveness of the weed. Further, this study identifies a crucial need for clearly defined biodiversity indicators from agro-ecologists and interdisciplinary efforts.

1.4 Conclusion and Recommendations

The aim of this thesis is to deepen the understanding of the interaction between farmers, SFTs and agricultural policy design, to inform decision-makers on how to leverage the potential of SFTs to support sustainable intensification of the agricultural sector. To this end, the three chapters of this thesis provide both theoretical, empirical and methodological contributions. The following section synthesizes the main findings of this thesis guided by the main research questions. By deriving recommendations for various stakeholders from this synthesis, Research Question 3 is answered.

1.4.1 *Research Question 1: What shapes farmers' behavior towards SFTs?*

Based on the findings from Chapters 2 and 3, we identify that social as well as personality factors play a crucial role in farmers' behavior towards SFTs. Further, we find that these factors are closely linked to the attributes of technology, namely observability and AI. We thereby fill important research gaps in understanding farmers' behavior towards SFTs in general and their information acquisition specifically. By applying a LASSO machine learning approach in Chapter 2, we demonstrate a clear link between the observability of a technology and social interactions as conceptually hypothesized by Shang et al. (2021). Observation of a technology seems to deliver information that differs from those obtained through verbal exchange. Yet a combination of verbal and visual information gathering comes with the highest likelihood of adoption, emphasizing the complementary nature of these two information sources. Based on the probabilistic programming workflow as detailed in Chapter 3, we can show that most farmers in our sample exhibit algorithm aversion. That means, most farmers prefer the human, even if it performs worse than the AI. In order to choose the AI-DST, it would have to be considerably cheaper than a human advisor while offering the same level of performance. We identify the underlying latent belief to be AI-anxiety.

Synthesizing these two results by drawing on the framework by Shang et al. (2021), a clear picture emerges: The source of information about a technology and about its potential costs and benefits is essential to induce a reduction of the perceived complexity [6] and thereby support adoption. Information from peers (verbally and visually) and from human advisors seem to be deemed as relevant for the decision-making process of farmers, but they perceive information from AI decision support rather skeptically. How information is processed seems to be associated with farmers' personality traits: A high AI-Anxiety correlates negatively with expectations concerning the complexity and also the performance of AI-based technology. As the perceived costs and benefits of a technology are an important adoption determinant (Déssart et al., 2019), we conclude that improvements in outcomes through SFT use need to be clearly demonstrated to make them attractive to farmers. The key to promoting the uptake of SFTs is to make the benefits easily recognizable, either by enabling the observation of results or by clearly communicating the benefits (e.g. the performance difference to human advice) to farmers.

[6] Depending on the theoretical framework, this technology attribute might also be considered as a latent construct termed “effort expectancy” in the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) or “ease of use” in the technology acceptance model (TAM) (Davis 1985).

1.4.2 *Research Question 2: What are the implications of SFTs for agricultural policy design?*

The novel abilities of SFTs open up for new policy designs, as revealed in Chapter 4. In contrast to previous literature, we find that not only the monitoring ability has the potential to induce changes in policy schemes design. But the technology attribute that mainly influences scheme design appears to be the ability to perform site- and time-specific tasks based on different rationales which enables more biodiversity-sensitive actions compared to broadband treatments. It allows for efficiency improvements of both ABS and RBS and triggers the need to rethink agricultural policy design. The line between executed actions, that farmers are paid for on the one and obtained pre-defined results, that are rewarded on the other hand, vanishes: Setting a weeding robot to executing a certain weeding strategy – for example to remove only those weeds that are highly competitive for the crop – could be either rewarded by ensuring that the defined strategy was executed (ABS) or by monitoring the occurrence of indicator weeds on the field (RBS).

1.4.3 *Research Question 3: What should optimal policy design look like to leverage the full potential of SFTs for sustainable intensification?*

Our findings and the answers to Research Question 1 and 2 emphasize the duality of the relationship between SFTs and agricultural policy. On the one hand, we show that SFTs have the potential to improve the efficiency of policy measures through monitoring, and time- and site-specific treatments. This might ease for example the implementation of RBS that require precise monitoring. On the other hand, we find that farmers seem to be reluctant to use AI-based SFTs despite their great potential for efficiency improvements, which prompts the need for policy measures. Results from two discrete choice experiments in Norway (Hillesund et al., 2025) [7] and Spain (Villanueva et al., 2024) underline this dilemma: farmers prefer the

[7] In this working paper, we analyzed Norwegian farmers' acceptance of collective results-based schemes using a discrete choice experiment. Anna Massfeller co-authored this working paper during her doctoral studies.

monitoring within an RBS to be done by a human rather than by a digital tool. Hence simply offering SFTs to farmers might not be enough to make them accept it. This observation calls for a clear need for policy measures that support farmers' adoption of SFTs.

However, technology adoption is only the first step. Once adopted, farmers also need to use the technology in the intended way. In Chapter 4 we build on the findings of Zingsheim and Döring (2024). They show that smart weeding robots – as an example of SFT – can contribute to sustainable intensification by substituting harmful inputs, such as chemical plant protection, with selective (mechanical) weeding. Selective weed removal also allows for a reduction in the trade-off between biodiversity and yield. However, these benefits will only materialize if farmers use the robots as intended, that means for targeted, selective weed removal. If not used selectively but instead operated like "traditional" tractor mounted machinery that treat the whole field homogeneously, future weeding robots will most probably remove weeds as efficiently and reliably as conventional, chemical approaches (Ahmadi et al., 2022). Consequently, the biodiversity on the field will be similarly low as under herbicide spraying. The same holds for the case of AI-DST: Our findings on algorithm aversion show, that the well-known "implementation problem" together with the issue of farmers owning tools but not using them (in the intended way) (McCown, 2002) seems to persist. Hence simply supporting farmers financially for adopting SFTs will not be enough, but guidance on how to use it is needed. Having these findings in mind, we derive our first policy recommendation:

Recommendation 1: Simply offering SFTs to farmers is not enough, decision-makers should develop measures that not only support but also guide farmers' use of SFTs such that the technologies' full potential to support a development towards sustainable intensification can be leveraged.

Having identified the need for effective policies, the question arises of how optimal policy measures could look like. The optimal choice of the tool depends on the relation between private and public benefit of the respective management practice (Pannell, 2008). Our findings from Chapter 3 show, farmers are reluctant to use AI-DST although they come with private and public benefits. This suggests the existence of learning costs, that is the cost of obtaining and analyzing information about the new technology, or the presence or absence of social networks that support learning (Pannell, 2008). The findings of this thesis provide clear insights on how social networks and information acquisition can reduce these learning costs and thereby trigger adoption of SFT. In Chapter 3 we find, that farmers would prefer an AI-DST only if it performs considerably better than a human. Hence information about the performance of SFT should be clearly communicated to the farmers to make them easily recognize the benefits. Alexander et al. (2018) found that social norms are even more effective in triggering AI adoption than providing information on the performance of the tool, accordingly combining information on benefits with a social aspect could prove efficient. As revealed in Chapter 2, to induce social learning, facilitating verbal and visual exchange among farmers to allow for low-threshold information acquisition is a promising mechanism. An important player in reducing learning costs and promoting the transformative capacity of the agricultural sector are extension services (Finger, 2023; Khanna, 2025). Based on the findings of this thesis we suggest that extension services should disseminate information about SFTs to reduce the expected effort and to raise awareness about potential benefits. Social learning could be supported through demonstration farms and organized farmer events that combine visual and verbal exchange. Here, other farmers can visit, exchange about potential costs and benefits and observe the technology in use and its outcomes. From Chapter 3, we learn that farmers are skeptical towards advice from AI despite its potential. Therefore AI-based tools may complement traditional extension services where deemed sufficiently efficient, but should be used with care. Consequently, we derive recommendation 2:

Recommendation 2: To promote the uptake of SFTs, decision-makers need to make benefits easily recognizable, for example by enabling social learning through the observation of and exchange about results.

For some SFT, there might be positive public benefits but negative private ones (i.e. costs). This is for example the case for smart weeding robots in conventional farming. Currently the private costs outweigh the private benefits for most conventional farmers, but public benefits in terms of a reduction of environmental degradation are assumed to be large (Shang et al., 2023). In such cases, reduced learning costs and extension might not be enough, but positive incentives are needed (Pannell, 2008). PES, action- or results-based, are one type of positive incentives where farmers are rewarded for providing public goods beyond regulatory standards. As we learned from Chapter 4, autonomous weeding robots might allow for efficiency increases in the design of PES for biodiversity conservation in arable farming. A major finding of this thesis is that, contrary to recent literature, not only RBS but also ABS can gain in efficiency when SFTs are available. In consequence, the difference in efficiency and also in design between ABS and RBS vanishes. The efficiency increase for ABS can be mainly traced back to the SFTs' ability to conduct time- and site-specific treatments that allow to decrease the trade-off between crop production and environmental degradation. Similarly, the efficiency increase for RBS stems from the improved monitoring and detection abilities. We therefore derive:

Recommendation 3: Decision-makers should leverage SFTs' abilities to improve the efficiency of PES with a focus on the potential from time- and site-specific treatment for ABS and from monitoring for RBS.

To more concretely answer the question of what optimal policy should look like in the era of smart farming, we first turn to ABS. By defining time- and site-specific actions that farmers are rewarded for, the environmental outcome could be ensured while the risk for the farmer would be kept at a minimal level. One concrete idea might be a weeding strategy (e.g. "Remove all weeds but species X, Y and Z") that a smart robot performs via software settings downloaded from the authorities. By letting the robot execute this strategy, the farmer receives a payment that compensates for potential costs. This approach touches on recent developments in research and the private sector towards so called "green insurances". Here, farmers receive a payment contingent on following recommendations from modern decision support tools (Lefebvre et al., 2025) or are compensated if crop health is not optimal although the recommendations have been followed (BASF, 2024). First evidence shows that this approach is accepted by farmers, easily traceable and allows for efficient food production while benefitting the environment (Lefebvre et al., 2025).

Concerning the design of RBS, the findings of this thesis suggest that SFT can help to monitor and identify plant and animal species autonomously and continuously and thereby reduce the risk of biodiversity benefits being present but not detected by human monitoring. Further, given the monitoring ability and the identified importance of the status quo of biodiversity before scheme participation, SFTs can unlock opportunities for novel payment mechanisms. Future RBS could reward farmers based on change, capacity, or proportionally to other farmers in the area (McDonald et al., 2018). That means, farmers are not paid for the absolute occurrence of indicator species on their fields, but rather for the relative occurrence compared to the status before scheme participation, or based on in how far the capacity of the field was reached based on modelled results (Bartkowski et al., 2021; Simpson et al., 2023). These approaches would not only reduce the (perceived) risk for the farmers of not reaching the predefined target (Burton & Schwarz, 2013), but they are dynamic and would allow the farmers as well as the authorities to adapt to the changing field and production conditions arising e.g. from climate change. In line with our second recommendation on social learning, evidence from Malawi suggests that offering a results-based scheme for specific farmers can induce social learning about this approach (e.g. when extension is costly) (BenYishay & Mobarak, 2019). For both, ABS and RBS, information on the desired outcome e.g. in terms of density, distribution and species selection of weeds is needed to either develop multidimensional indicators for RBS or to define concrete treatment strategies for ABS e.g. which weeds to remove and why.

Besides, a rather general conclusion that follows from the findings of this thesis concerns measures beyond the single farm level, as many ecosystem services like biodiversity abundance depend heavily on the composition and configuration of the whole landscape (Batáry et al., 2020; Tscharntke et al., 2012). Therefore, engagement among several farmers within a region is required. In Chapter 2 we identify the importance of peer effects, as verbal exchange and field observation mutually reinforce each other. In Chapter 4 we show how RBS might become an important element of the CAP toolbox given the abilities of SFTs. Combined, these findings call for policy measures that combine the RBS character with a collective feature that allows farmers to interact through agglomeration schemes or collective bonus schemes, as e.g. implemented in Switzerland (Huber et al., 2021; Sander et al., 2024). Besides other advantages, investment costs could be reduced through shared ownership structures. A recent study with Norwegian farmers found that combining RBS with a collective aspect might be promising, especially for rather small groups of 3 to 6 farmers (Hillesund et al., 2025). Novel SFTs might support the implementation of such collective results-based measures by easing communication among stakeholders and facilitating planning and monitoring (Geppert et al., 2023, 2024; Reichenspurner & Matzdorf, 2025), which might also reduce the bureaucratic burden, one main barrier to adoption of RBS (Massfeller et al., 2022)[8]. We therefore derive recommendation 4:

Recommendation 4: To design efficient policies, decision-makers should closely collaborate with agro-ecologists and leverage SFTs' potential to benefit combinations of action- and results-based measures at the farm and landscape-level.

Lastly, technological development is needed where private costs are clearly higher than public benefits (Pannell, 2008). That means technologies that are promising from an environmental perspective need to become attractive to farmers by providing clear private benefits. As revealed in Chapter 3 of this thesis, wether a technology is perceived as attractive depends strongly on the expected effort to use the technology and its expected performance. We therefore suggest that technology developers should try to reduce the complexity of SFTs and make it easy to use for farmers. Further, one specific challenge for the case of biodiversity conservation resulting from the second recommendation is that public as well as private benefits are often hard to predict, to measure and hence to perceive (Kidd et al., 2019; Kleijn et al., 2019). SFTs might help to overcome this issue not only through improved monitoring but also by allowing for a clear communication of biodiversity metrics. These could also be used as direct feedback on the potential and obtained ecological and economic implications of a specific management to

[8] In this article, German farmers' acceptance of a hybrid results-based scheme for arable farming is investigated using a split treatment experimental design to test the effect of a social nudge. Anna Massfeller co-authored this paper during the beginning of her doctoral studies, however, it is not included as a main chapter in this thesis.

the farmers. Such “green nudges” have been proven efficient in other contexts (cf. Peth et al., 2018) but could so far not be implemented for biodiversity conservation due to the difficulty of measuring benefits. Coming back to the social aspect in farmers’ technology adoption decision, farmers or authorities could use the measured biodiversity metrics to signal environmental engagement to other farmers or the public, e.g. via signs in the field, as social signaling is a major determinant in farmers’ decision-making (Déssart et al., 2019). We therefore propose the development of user-friendly interfaces that allow for transparent communication of potential and achieved ecological and economic benefits. Given the findings on the importance of site- and time-specific treatments in Chapter 4, we further claim that technology developers should consider reduction of trade-offs between crop production and environmental degradation. For example, a weeding robot should not only be able to remove weeds efficiently, but also selectively based on different rationales. Consequently, recommendation 5 follows:

Recommendation 5: Technology developers should leverage the potential of SFTs to reduce trade-offs and to make private and public ecological and economic benefits easily recognizable through user-friendly interfaces, thereby contributing to sustainable intensification.

1.5 **Limitations and Outlook**

The following section reflects on two general limitations of this dissertation at a synthesized level, to then derive future research avenues. More details on each study’s specific constraints are provided in the respective chapters.

1.5.1 *Limitations*

A general limitation of studies based on primary data is the size and the composition of the sample. For both studies (in Chapter 2 and Chapter 3), we work together with the market research company “agri experts” (agri experts – Deutscher Landwirtschaftsverlag GmbH, 2023), that rely on a large pool of farmers and publish advertisements for their surveys in print and online magazines and websites that belong to their publishing house.

While many farmers all over Germany are reached, a certain self-selection bias might occur. This concerns for example the age of the population, as younger farmers might be more prone to participate in online surveys (Zahl-Thanem et al., 2021). We carefully check the representativeness of observable characteristics and account for this potential bias by including them as a control variable in our models. Further, concerning limitations in statistical meaningfulness due to small sample sizes, as part of good scientific practice, we conducted an a-priori power analysis for the study in Chapter 2 to transparently determine the detectable effect size. In Chapter 3 we use Bayesian probabilistic programming, which allows inference on model parameters even with small sample sizes, due to the explicit formulation of prior knowledge.

In consequence, our results from the observational study in Chapter 2 show high external validity while the experimental setting in Chapter 3 ensures high internal validity in light of the assumptions made. But evidence on how contextual framing affects external validity and farmers' comprehension in experiments is mixed (Rommel et al., 2017, 2019). Therefore, to further validate our findings, the questions we highlight through our studies need to be investigated in future research. Hereby, our innovative approaches and the results can serve as basis for these future research endeavors, for example by using the survey tool we designed to capture peer effects on an interactive map by a larger sample or by following the probabilistic programming workflow for experimental studies.

A second general limitation of this thesis concerns the restricted choice of SFTs as we focus only on two technologies, smart weeding robots and AI-DST. Other technologies with different characteristics might lead to different findings and resulting implications and recommendations (Martinsson & Storm, 2025). Therefore, future research could investigate other SFTs by relying on our procedures. For example, the simulation study in Chapter 4 could be modified to reflect the use of a drone for monitoring biodiversity abundance. Similarly, the survey tool we developed in Chapter 2 to capture peer effects via an interactive map could be employed to study the roel of peer effects in the adoption of other SFTs that are broadly in use like automatic milking systems (Vik et al., 2019). The experiment in Chapter

3 could be adapted to study if farmers' algorithm aversion differs for other AI-based tools supporting for example coordination of collective policy schemes (see first examples by Geppert et al., 2024; Reichenspurner & Matzdorf, 2025).

1.5.2 *Future research avenues*

Besides the research needs resulting from the general limitations, we derive two concrete future research avenues arising from the findings of this thesis.

First, we suggest that future research should develop and test a (at first hypothetical) "robot-based PES", in which farmers are rewarded for using a weeding robot in a specified way. Different payment structures could be tested: On the one hand, farmers might receive results-based payments for some multi-dimensional biodiversity indicator. This indicator can be based on the absolute abundance, on the change obtained, or the capacity reached of these pre-defined indicators. On the other hand, farmers could receive action-based payments that depend on a certain weeding strategy the robot is set to. Here, one specific idea for a weeding strategy would be to rely on weed removal based on crop row, an approach that has been proven efficient in improving the trade-off between yield and biodiversity (Zingsheim & Döring, 2024) and was hypothetically accepted by farmers in form of a hybrid scheme (combination of action- and results-based elements) (Massfeller et al., 2022). Such research should be carried out in close collaboration with agro-ecologists that clearly identify multi-dimensional indicators (e.g. which weed species at what density and distribution) and technology developers that ensure weeding robots are able to execute the required weeding strategies.

Second, another research avenue evolves from the synthesis of all three chapters: the value of information and farmers' information processing. Throughout this thesis we identify the importance of information about benefits of a technology for its adoption. As shown in Chapter 2 and Chapter 3, farmers rely on information from peers and (human and digital) advisory services in order to optimize their crop management decisions. In Chapter 4 we have discussed how SFTs can provide information that might guide farmers' use in a certain way e.g. when information on biodiversity at field level is given in form of a green nudge. In light of the increasing amount of data that can be collected by novel SFTs and then communicated to farmers, it is important to understand how farmers process such information and which they deem as relevant for their decisions to adopt sustainable farming practices, technologies or policy measures. This valuation of information is known as epistemic vigilance (Bielik & Krell, 2025; Sperber et al., 2010)). However, to date, little is known about farmers' epistemic vigilance. With this thesis, we gain first insights into farmers' epistemic vigilance, focusing on the source (Peers in Chapter 2, AI vs. human in Chapter 3) and the characteristics of the receiver (AI-Anxiety as inherent individual belief in Chapter 3), but future research should further investigate this topic.

1.6 References

Acemoglu, D. (2002). Directed technical change. *The Review of Economic Studies*, *69*(4), 781–809.

agri experts – Deutscher Landwirtschaftsverlag GmbH. (2023, April 27). *agri experts: Marktforschung im Agrar Bereich*. Agri Experts; DLV. https://www.agri-experts.de/en/about-agri-experts/

Ahmadi, A., Halstead, M., & McCool, C. (2022). BonnBot-I: A Precise Weed Management and Crop Monitoring Platform. *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 9202–9209.

Albizua, A., Bennett, E. M., Larocque, G., Krause, R. W., & Pascual, U. (2021). Social networks influence farming practices and agrarian sustainability. *PloS One*, *16*(1), e0244619.

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

Bandiera, O., & Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal of Nepal*, *116*(514), 869–902.

Bartkowski, B., & Bartke, S. (2018). Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. *Sustainability: Science Practice and Policy*, *10*(9), 3179.

Bartkowski, B., Droste, N., Ließ, M., Sidemo-Holm, W., Weller, U., & Brady, M. V. (2021). Payments by modelled results: A novel design for agri-environmental schemes. *Land Use Policy*, *102*, 105230.

Basavegowda, D., Schleip, I., Dorothea Bellingrath-Kimura, S., & Weltzien, C. (2025). UAV-assisted deep learning to support results-based agri-environmental schemes: Facilitating Eco-Scheme 5 implementation in Germany. *Biological Conservation*, *309*(111323), 111323.

BASF. (2024). *xarvio HEALTHY FIELDS*. https://www.xarvio.com/de/de/products/healthy-fields.html

Batáry, P., Báldi, A., Ekroos, J., Gallé, R., Grass, I., & Tscharntke, T. (2020). Biologia Futura: landscape perspectives on farmland biodiversity conservation. *Biologia Futura*, *71*(1–2), 9–18.

Bawden, O., Kulk, J., Russell, R., McCool, C., English, A., Dayoub, F., Lehnert, C., & Perez, T. (2017). Robot for weed species plant-specific management. *Journal of Field Robotics*, *34*(6), 1179–1199.

Belloni, A., & Chernozhukov, V. (2014). Inference on treatment effects after selection among high-dimensional controls. *The Review of Economic*. https://academic.oup.com/restud/article-abstract/81/2/608/1523757

Belloni, Alexandre, Chernozhukov, V., & Hansen, C. (2014). High-Dimensional Methods and Inference on Structural and Treatment Effects. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *28*(2), 29–50.

BenYishay, A., & Mobarak, A. M. (2019). Social Learning and Incentives for Experimentation and Communication. *The Review of Economic Studies*, *86*(3), 976–1009.

Besley, T., & Case, A. (1993). Modeling Technology Adoption in Developing Countries. *The American Economic Review*, *83*(2), 396–402.

Besson, M., Alison, J., Bjerge, K., Gorochowski, T. E., Høye, T. T., Jucker, T., Mann, H. M. R., & Clements, C. F. (2022). Towards the fully automated monitoring of ecological communities. *Ecology Letters*, *25*(12), 2753–2775.

Bielik, T., & Krell, M. (2025). Developing and evaluating the extended epistemic vigilance framework. *Journal of Research in Science Teaching*, *62*(3), 869–895.

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

BLE. (2018). *Integrierter Pflanzenschutz*. Bundesanstalt für Landwirtschaft und Ernährung. https://www.nap-pflanzenschutz.de/fileadmin/SITE_MASTER/content/IPS/Integrierter_Pflanzenschutz/Entscheidungshilfen/BZL_Heft_IntegrierterPflanzenschutz_Mai2018.pdf

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., Wuepper, D., Montanarella, L., and Ballabio, C. (2020). Land use and climate change impacts on global soil erosion by water (2015-2070). *Proceedings of the National Academy of Sciences of the United States of America* 117: 21994–22001.

Bramoullé, Y., Djebbari, H., & Fortin, B. (2020). Peer Effects in Networks: A Survey. *Annual Review of Economics*, *12*(1), 603–629.

Brown, C., Kovács, E., Herzon, I., Villamayor-Tomas, S., Albizua, A., Galanaki, A., Grammatikopoulou, I., McCracken, D., Olsson, J. A., & Zinngrebe, Y. (2021). Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. *Land Use Policy*, *101*, 105136.

Burton, R. J. F., & Schwarz, G. (2013). Result-oriented agri-environmental schemes in Europe and their potential for promoting behavioural change. *Land Use Policy*, *30*(1), 628–641.

Caiado, R. G. G., Freitas Dias, R., Mattos, L. V., Quelhas, O. L. G., & Leal Filho, W. (2017). Towards sustainable development through the perspective of eco-efficiency - A systematic literature review. *Journal of Cleaner Production*, *165*, 890–904.

Campbell, B. M., Beare, D. J., Bennett, E. M., Hall-Spencer, J. M., Ingram, J. S. I., Jaramillo, F., Ortiz, R., Ramankutty, N., Sayer, J. A., & Shindell, D. (2017). Agriculture production as a major driver of the Earth system exceeding planetary boundaries. *Ecology and Society: A Journal of Integrative Science for Resilience and Sustainability*, *22*(4). https://doi.org/10.5751/es-09595-220408

Chaplin, S. P., Mills, J., & Chiswell, H. (2021). Developing payment-by-results approaches for agri-environment schemes: Experience from an arable trial in England. *Land Use Policy*, *109*, 105698.

Chavas, J., & Nauges, C. (2020). Uncertainty, Learning, and Technology Adoption in Agriculture. *Applied Economic Perspectives and Policy*, *42*(1), 42–53.

Conley, & Udry. (2010). Learning about a New Technology: Pineapple in Ghana. *The American Economic Review*, *100*(1), 35–69.

Daum, T. (2021). Farm robots: ecological utopia or dystopia? *Trends in Ecology & Evolution*, *36*(9), 774–777.

De la Peña, N., & Granados, O. M. (2024). Artificial intelligence solutions to reduce information asymmetry for Colombian cocoa small-scale farmers. *Information Processing in Agriculture*, *11*(3), 310–324.

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

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: people erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology. General*, *144*(1), 114–126.

Ehlers, M.-H., Finger, R., El Benni, N., Gocht, A., Sørensen, C. A. G., Gusset, M., Pfeifer, C., Poppe, K., Regan, Á., Rose, D. C., Wolfert, S., & Huber, R. (2022). Scenarios for European agricultural policymaking in the era of digitalisation. *Agricultural Systems*, *196*, 103318.

Ehlers, M.-H., Huber, R., & Finger, R. (2021). Agricultural policy in the era of digitalisation. *Food Policy*, *100*, 102019.

Elmiger, B. N., Finger, R., Ghazoul, J., & Schaub, S. (2023). Biodiversity indicators for result-based agri-environmental schemes – Current state and future prospects. *Agricultural Systems*, *204*(103538), 103538.

European Commission. (2020a). *Farm to Fork Strategy*. https://eur-lex.europa.eu/resource.html?uri=cellar:ea0f9f73-9ab2-11ea-9d2d-01aa75ed71a1.0001.02/DOC_1&format=PDF

European Commission. (2020b). *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

European Commission. (2021). *EU biodiversity strategy for 2030 – Bringing nature back into our lives*. Directorate-General for Environment,European Commission. https://data.europa.eu/doi/10.2779/677548

Eurostat. (2025a). Employment by detailed industry (NACE Rev.2) - national accounts [Data set]. In *nama_10_a64_e*. https://ec.europa.eu/eurostat/databrowser/view/nama_10_a64_e__custom_17546951/default/table

Eurostat. (2025b). Land use overview by NUTS 2 region [Data set]. In *lan_use_ovw*. https://ec.europa.eu/eurostat/databrowser/view/lan_use_ovw__custom_17547032/default/table

FAO. (2024). *The state of food and agriculture 2024*. FAO. https://doi.org/10.4060/cd2616en

FAO. (2025a). *Crops and livestock products - Yields* [Data set]. https://www.fao.org/faostat/en/#data/QCL

FAO. (2025b). *Pesticides Use - Agricultural Use* [Data set]. https://www.fao.org/faostat/en/#data/RP

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, *33*(2), 255–298.

Feisthauer, P., Hartmann, M., & Börner, J. (2024). Behavioral factors driving farmers' intentions to adopt spot spraying for sustainable weed control. *Journal of Environmental Management*, *353*, 120218.

Fennimore, S. A., & Cutulle, M. (2019). Robotic weeders can improve weed control options for specialty crops. *Pest Management Science*, *75*(7), 1767–1774.

Finch, W. H., & Hernandez Finch, M. E. (2016). Regularization methods for fitting linear models with small sample sizes: Fitting the lasso estimator using R. In *Practical Assessment, Research, and Evaluation*. University of Massachusetts Amherst. https://doi.org/10.7275/JR3D-CQ04

Finger, Benni, E., Kaphengst, Sauter, & Sieber. (2019). Relevance of adoption and control of innovative technologies in agriculture for policy design. *Agricultural Economics*, *50*(3), 299–310.

Finger, R. (2023). Digital innovations for sustainable and resilient agricultural systems. *European Review of Agricultural Economics*. https://doi.org/10.1093/erae/jbad021

Finger, R., Fabry, A., Kammer, M., Candel, J., Dalhaus, T., & Meemken, E. M. (2024). Farmer protests in Europe 2023–2024. *EuroChoices*. https://doi.org/10.1111/1746-692x.12452

Finger, R., Henningsen, A., Höhler, J., Huber, R., Rommel, J., & Grebitus, C. (2024). Open science in agricultural economics. *Q Open*. https://doi.org/10.1093/qopen/qoae029

Finger, R., & Möhring, N. (2022). The adoption of pesticide-free wheat production and farmers' perceptions of its environmental and health effects. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *198*, 107463.

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *The Journal of Political Economy*, *103*(6), 1176–1209.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of Technology Adoption. *Annual Review of Economics*, *2*. https://doi.org/10.1146/annurev.economics.102308.124433

Fritsch, C., Berny, P., Crouzet, O., Le Perchec, S., & 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*. https://doi.org/10.1007/s11356-024-33026-1

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*(2), 97–105.

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

Geppert, F., Bellingrath-Kimura, S., & Mouratiadou, I. (2023). Fostering the implementation of nature conservation measures in agricultural landscapes: The NatApp. *Sustainability*. https://doi.org/10.3390/su15043030

Geppert, F., Krachunova, T., Mouratiadou, I., von der Nuell, J., & Bellingrath-Kimura, S. D. (2024). Digital and smart technologies to enhance biodiversity in agricultural landscapes: An analysis of stakeholders' perceptions of opportunities and challenges for broader adoption. *Environmental and Sustainability Indicators*, *23*(100444), 100444.

Gianessi, L., & Williams, A. (2011). *Europe's wheat yields are the world's highest due to fungicide use*. https://croplife.org/wp-content/uploads/pdf_files/Europes-wheat-yields-are-the-worlds-highest-due-to-fungicide-use.pdf

Gibbons, J. M., Nicholson, E., Milner-Gulland, E. J., & Jones, J. P. G. (2011). Should payments for biodiversity conservation be based on action or results? *The Journal of Applied Ecology*, *48*(5), 1218–1226.

Giulivi, N., Harou, A. P., Gautam, S., & Guereña, D. (2023). Getting the message out: Information and communication technologies and agricultural extension. *American Journal of Agricultural Economics*, *105*(3), 1011–1045.

Gouel, C., and Guimbard, H. (2019). Nutrition transition and the structure of global food demand. *American Journal of Agricultural Economics* 101: 383–403.

Hagemann, N., Gerling, C., Hölting, L., Kernecker, M., Markova-Nenova, N. N., Wätzold, F., Wendler, J., & Cord, A. F. (2025). Improving result-based schemes for nature conservation in agricultural landscapes—challenges and best practices from selected European countries. *Regional Environmental Change*, *25*(1). https://doi.org/10.1007/s10113-024-02324-2

Helps, J. C., van den Bosch, F., Paveley, N., Jørgensen, L. N., Holst, N., & Milne, A. E. (2024). A framework for evaluating the value of agricultural pest management decision support systems. *European Journal of Plant Pathology*, *169*(4), 887–902.

Herzon, I., Birge, T., Allen, B., Povellato, A., Vanni, F., Hart, K., Radley, G., Tucker, G., Keenleyside, C., Oppermann, R., Underwood, E., Poux, X., Beaufoy, G., & Pražan, J. (2018). Time to look for evidence: Results-based approach to biodiversity conservation on farmland in Europe. *Land Use Policy*, *71*, 347–354.

Hicks, J. R., & Simiand, F. (1932). Le Salaire, l'Evolution Sociale et la Monnaie. Essai de Theorie Experimentale du Salaire. *Economic Journal (London, England)*, *42*(167), 451.

Hillesund, R. S., Massfeller, A. T., Mittenzwei, K., & Kokemohr, L. (2025). Norwegian Farmers' Preferences for Collective Results-based Agri-environmental Schemes: a Discrete-choice Experiment. *Conference Paper Submitted to EAAE 2025*. EAAE 2025.

Hossain, L., Rahman, R., & Khan, M. S. (2017). Alternatives of Pesticides. In M. S. Khan & M. S. Rahman (Eds.), *Pesticide Residue in Foods: Sources, Management, and Control* (pp. 147–165). Springer International Publishing.

Huber, R., Zabel, A., Schleiffer, M., Vroege, W., Brändle, J. M., & Finger, R. (2021). Conservation Costs Drive Enrolment in Agglomeration Bonus Scheme. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *186*, 107064.

IPCC. (2022). *Climate Change and Land: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land*

Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems. Cambridge University Press.

Kehoe, L., Senf, C., Meyer, C., Gerstner, K., Kreft, H., & Kuemmerle, T. (2017). Agriculture rivals biomes in predicting global species richness. *Ecography*, *40*(9), 1118–1128.

Khanna, M. (2025, April 28). *Artificial intelligence-based digital technologies for sustainable agriculture*. DIGICROP2025. https://digicrop.de/madhu-khanna/index.html

Khanna, M., Atallah, S. S., Heckelei, T., Wu, L., & Storm, H. (2024). Economics of the adoption of artificial intelligence–based digital technologies in agriculture. *Annual Review of Resource Economics*. https://doi.org/10.1146/annurev-resource-101623-092515

Kidd, L. R., Garrard, G. E., Bekessy, S. A., Mills, M., Camilleri, A. R., Fidler, F., Fielding, K. S., Gordon, A., Gregg, E. A., Kusmanoff, A. M., Louis, W., Moon, K., Robinson, J. A., Selinske, M. J., Shanahan, D., & Adams, V. M. (2019). Messaging matters: A systematic review of the conservation messaging literature. *Biological Conservation*, *236*, 92–99.

Kiraly, G., Vago, S., Bull, E., Cruyssen, L. van der, Arbour, T., Spanoghe, P., & 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/

Kleijn, D., Bommarco, R., Fijen, T. P. M., Garibaldi, L. A., Potts, S. G., & van der Putten, W. H. (2019). Ecological Intensification: Bridging the Gap between Science and Practice. *Trends in Ecology & Evolution*, *34*(2), 154–166.

Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of Agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security*, *24*, 100347.

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

Lefebvre, M., Raineau, Y., Aubert, C., Möhring, N., Pedehour, P., & Raynal, M. (2025). Green insurance for pesticide reduction:

Acceptability and impact for French viticulture. *European Review of Agricultural Economics*. https://doi.org/10.1093/erae/jbaf002

Leyens, A. F., Philipp Börner, J., Hartmann, M., & Storm, H. (2024). Round effects in economic experiments - A novel probabilistic programming approach to timevariant response behaviour. *Agricultural Economics Society - AES > 98th Annual Conference, March 18-20, 2024, The University of Edinburgh, Edinburgh, UK*. https://doi.org/10.22004/AG.ECON.355341

Lindblom, J., Lundström, C., Ljung, M., & Jonsson, A. (2017). Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precision Agriculture*, *18*(3), 309–331.

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

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, *60*(3), 531.

Markova-Nenova, N., Engler, J. O., Cord, A. F., & Wätzold, F. (2023). Will passive acoustic monitoring make result-based payments more attractive? A cost comparison with human observation for farmland bird monitoring. *Conservation Science and Practice*, *5*(9). https://doi.org/10.1111/csp2.13003

Martinsson, E., & Storm, H. (2025). Conceptualization of how Adopting Novel Technology Induces Structural and Behavioural Changes on Farms. *Journal of Agricultural and Resource Economics: Preprint*. https://doi.org/10.22004/ag.econ.35616

Massfeller, A., Meraner, M., Hüttel, S., & Uehleke, R. (2022). Farmers' acceptance of results-based agri-environmental schemes: A German perspective. *Land Use Policy*, *120*, 106281.

Massfeller, A., & Storm, H. (2024). Field observation and verbal exchange as different peer effects in farmers' technology adoption decisions. *Agricultural Economics (Amsterdam, Netherlands)*, *55*(5), 739–757.

Massfeller, A., Zingsheim, M., Ahmadi, A., Martinsson, E., & Storm, H. (2025). Action- or results-based payments for ecosystem services in the era of smart weeding robots? *Biological Conservation, 302*, 110998.

McCann, L., Gedikoglu, H., Broz, B., Lory, J., & Massey, R. (2015). Effects of observability and complexity on farmers' adoption of environmental practices. *Journal of Environmental Planning and Management*, *58*(8), 1346–1362.

McCown, R. L. (2002). Changing systems for supporting farmers' decisions: problems, paradigms, and prospects. *Agricultural Systems*, *74*(1), 179–220.

McDonald, J. A., Helmstedt, K. J., Bode, M., Coutts, S., McDonald-Madden, E., & Possingham, H. P. (2018). Improving private land conservation with outcome-based biodiversity payments. *The Journal of Applied Ecology*, *55*(3), 1476–1485.

McElreath, R. (2018). *Statistical rethinking: A Bayesian course with examples in R and Stan*. Chapman and Hall/CRC.

Mekonnen, D. K., Yimam, S., Arega, T., Matheswaran, K., & Schmitter, P. M. V. (2022). Relatives, neighbors, or friends: Information exchanges among irrigators on new on-farm water management tools. *Agricultural Systems*, *203*, 103492.

Mennig, P. (2024). A never-ending story of reforms: on the wicked nature of the Common Agricultural Policy. *NPJ Sustainable Agriculture*, *2*(1), 1–7.

Meyer, M., Schaub, S., & Bonev, P. (2025). Woody plant encroachment, grassland loss, and farm subsidies. *Journal of Agricultural Economics*. https://doi.org/10.1111/1477-9552.12641

Nause, N., Strassemeyer, J., Mahlein, A.-K., and Stockfisch, N. (2021). Pesticide use in sugar beet cultivation in Germany and assessment of the associated environmental risks using the risk indicator SYNOPS-GIS. *Pest Management Science* 77: 4614–4626.

Noy, S., & Jabbour, R. (2020). Decision-Making in Local Context: Expertise, Experience, and the Importance of Neighbours in Farmers' Insect Pest Management. *Sociologia Ruralis*, *60*(1), 3–19.

OECD. (2019). *The digital transformation of the agriculture and food system*. https://www.oecd.org/content/dam/oecd/en/publications/reports/2019/11/the-digital-transformation-of-the-agriculture-and-food-system_08e94d56/7a94280c-en.pdf

Oerke, E.-C. (2006). Crop losses to pests. *The Journal of Agricultural Science*, *144*(1), 31–43.

Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change* 11: 306–312.

Orn, D., Duan, L., Liang, Y., Siy, H., & Subramaniam, M. (2020, October 7). Agro-AI education: Artificial intelligence for future farmers. *Proceedings of the 21st Annual Conference on Information Technology Education*. SIGITE '20: The 21st Annual Conference on Information Technology Education, Virtual Event USA. https://doi.org/10.1145/3368308.3415457

Pannell, D. J. (2008). Public Benefits, Private Benefits, and Policy Mechanism Choice for Land-Use Change for Environmental Benefits. *Land Economics*, *84*(2), 225–240.

Pannell, D. J., & Claassen, R. (2020). The roles of adoption and behavior change in agricultural policy. *Applied Economic Perspectives and Policy*, *42*(1), 31–41.

Pe'er, G., Zinngrebe, Y., Hauck, J., Schindler, S., Dittrich, A., Zingg, S., Tscharntke, T., Oppermann, R., Sutcliffe, L. M. E., Sirami, C., Schmidt, J., Hoyer, C., Schleyer, C., & Lakner, S. (2017). Adding some green to the greening: Improving the EU's ecological focus areas for biodiversity and farmers. *Conservation Letters*, *10*(5), 517–530.

Pendrill, F., Gardner, T. A., Meyfroidt, P., Persson, U. M., Adams, J., Azevedo, T., Bastos Lima, M. G., Baumann, M., Curtis, P. G., De Sy, V., Garrett, R., Godar, J., Goldman, E. D., Hansen, M. C., Heilmayr, R., Herold, M., Kuemmerle, T., Lathuillière, M. J., Ribeiro, V., … West, C. (2022). Disentangling the numbers behind agriculture-driven tropical deforestation. *Science (New York, N.Y.)*, *377*(6611), eabm9267.

Peth, D., Mußhoff, O., Funke, K., & Hirschauer, N. (2018). Nudging Farmers to Comply With Water Protection Rules – Experimental Evidence From Germany. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *152*, 310–321.

Reichenspurner, M., & Matzdorf, B. (2025). Smart landscape diversification? Farmers' perspectives on how digital tools can facilitate (collective) agri-environmental action in Brandenburg, Germany. *Biological Conservation*, *306*(111108), 111108.

Richardson, K., Steffen, W., Lucht, W., Bendtsen, J., Cornell, S. E., Donges, J. F., Drüke, M., Fetzer, I., Bala, G., von Bloh, W., Feulner, G., Fiedler, S., Gerten, D., Gleeson, T., Hofmann, M., Huiskamp, W., Kummu, M., Mohan, C., Nogués-Bravo, D., … Rockström, J. (2023). Earth beyond six of nine planetary boundaries. *Science Advances*, *9*(37), eadh2458.

Rogers, E. M. (2003). *DIFFUSION OF INNOVATIONS: Vol. 5th Edition*. Free Press.

Rommel, J., Hermann, D., Müller, M., & Mußhoff, O. (2017). Comprehension in risk elicitation experiments. *Applied Economics Letters*, *24*(9), 627–634.

Rommel, J., Hermann, D., Müller, M., & Mußhoff, O. (2019). Contextual framing and monetary incentives in field experiments on risk preferences: Evidence from German farmers. *Journal of Agricultural Economics*, *70*(2), 408–425.

Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*, *2*. https://doi.org/10.3389/fsufs.2018.00087

Russi, D., Margue, H., Oppermann, R., & Keenleyside, C. (2016). Result-based agri-environment measures: Market-based instruments, incentives or rewards? The case of Baden-Württemberg. *Land Use Policy*, *54*, 69–77.

Sampson, G. S., & Perry, E. D. (2019). The role of peer effects in natural resource appropriation – the case of groundwater. *American Journal of Agricultural Economics*, *101*(1), 154–171.

Sander, A., Ghazoul, J., Finger, R., & Schaub, S. (2024). Participation in individual and collective agri-environmental schemes: A synthesis using the Theory of Planned Behaviour. *Journal of Rural Studies*, *107*(103255), 103255.

Schilizzi, S., Breustedt, G., & Latacz-Lohmann, U. (2011). *Does tendering conservation contracts with performance payments generate additional benefits?* ageconsearch.umn.edu. https://ageconsearch.umn.edu/record/100883/

Schroeder, L. A., Isselstein, J., Chaplin, S., & Peel, S. (2013). Agri-environment schemes: Farmers' acceptance and perception of potential 'Payment by Results' in grassland—A case study in England. In *Land Use Policy* (Vol. 32, pp. 134–144). https://doi.org/10.1016/j.landusepol.2012.10.009

Schulz, D., & Börner, J. (2022). Innovation context and technology traits explain heterogeneity across studies of agricultural technology adoption: A meta-analysis. *Journal of Agricultural Economics*. https://doi.org/10.1111/1477-9552.12521

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction. *Agricultural Systems*, *190*, 103074.

Shang, L., Pahmeyer, C., Heckelei, T., Rasch, S., & Storm, H. (2023). How much can farmers pay for weeding robots? A Monte Carlo simulation study. *Precision Agriculture*. https://doi.org/10.1007/s11119-023-10015-x

Simpson, K., Armsworth, P. R., Dallimer, M., Nthambi, M., de Vries, F. P., & Hanley, N. (2023). Improving the ecological and economic performance of agri-environment schemes: Payment by modelled results versus payment for actions. *Land Use Policy*, *130*, 106688.

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

Slaughter, D. C., Giles, D. K., & Downey, D. (2008). Autonomous robotic weed control systems: A review. *Computers and Electronics in Agriculture*, *61*(1), 63–78.

Sperber, D., Clément, F., Heintz, C., Mascaro, O., Mercier, H., Origgi, G., & Wilson, D. (2010). Epistemic vigilance. *Mind & Language*, *25*(4), 359–393.

Storm, H., Baylis, K., & Heckelei, T. (2019). Machine learning in agricultural and applied economics. *European Review of Agricultural Economics*, *47*(3), 849–892.

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

Storm, H., Seidel, S. J., Klingbeil, L., Ewert, F., Vereecken, H., Amelung, W., Behnke, S., Bennewitz, M., Börner, J., Döring, T., Gall, J., Mahlein, A.-K., McCool, C., Rascher, U., Wrobel, S., Schnepf, A., Stachniss, C., & Kuhlmann, H. (2024). Research priorities to leverage smart digital technologies for sustainable crop production. *European Journal of Agronomy: The Journal of the European Society for Agronomy*, *156*(127178), 127178.

Stranieri, S., Varacca, A., Casati, M., Capri, E., & 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*(7), 33–48.

Streletskaya, N. A., Bell, S. D., Kecinski, M., Li, T., Banerjee, S., Palm-Forster, L. H., & Pannell, D. (2020). Agricultural adoption and behavioral economics: Bridging the gap. *Applied Economic Perspectives and Policy*. https://doi.org/10.1002/aepp.13006

Šūmane, S., Kunda, I., Knickel, K., Strauss, A., Tisenkopfs, T., Des Rios, I. I., Rivera, M., Chebach, T., & Ashkenazy, A. (2018). Local and farmers' knowledge matters! How integrating informal and formal knowledge enhances sustainable and resilient agriculture. *Journal of Rural Studies*, *59*, 232–241.

Tang, F. H. M., Lenzen, M., McBratney, A., & Maggi, F. (2021). Risk of pesticide pollution at the global scale. *Nature Geoscience*, *14*(4), 206–210.

Tjernström, E. (2017). *Signals, Similarity and Seeds: Social Learning in the Presence of Imperfect Information and Heterogeneity. In Learning for Adopting: Technology Adoption in Developing Country Agriculture* (A. De Janvry, K. Macours, E. Sadoulet, & France, Eds.).

Tscharntke, T., Tylianakis, J. M., Rand, T. A., Didham, R. K., Fahrig, L., Batáry, P., Bengtsson, J., Clough, Y., Crist, T. O., Dormann, C. F., Ewers, R. M., Fründ, J., Holt, R. D., Holzschuh, A., Klein, A. M., Kleijn, D., Kremen, C., Landis, D. A., Laurance, W., … Westphal, C. (2012). Landscape moderation of biodiversity patterns and processes - eight hypotheses. *Biological Reviews of the Cambridge Philosophical Society*, *87*(3), 661–685.

Tubiello, F. N., Karl, K., Flammini, A., Gütschow, J., Obli-Laryea, G., Conchedda, G., Pan, X., Qi, S. Y., Halldórudóttir Heiðarsdóttir, H., Wanner, N., Quadrelli, R., Rocha Souza, L., Benoit, P., Hayek, M., Sandalow, D., Mencos Contreras, E., Rosenzweig, C., Rosero Moncayo, J., Conforti, P., & Torero, M. (2022). Pre- and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. *Earth System Science Data*, *14*(4), 1795–1809.

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

Vik, J., Stræte, E. P., Hansen, B. G., & Nærland, T. (2019). The political robot – The structural consequences of automated milking systems (AMS) in Norway. *NJAS - Wageningen Journal of Life Sciences, 90–91*, 100305.

Villanueva, A. J., Granado-Díaz, R., & Colombo, S. (2024). Comparing practice- and results-based agri-environmental schemes controlled by remote sensing: An application to olive groves in Spain. *Journal of Agricultural Economics*. https://doi.org/10.1111/1477-9552.12573

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

Wang, Y.-Y., & 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*(4), 619–634.

Warnecke-Busch, G., Mücke, M., & Others. (2020). Mechanical and mechanical-chemical weed control in sugar beets (Beta vulgaris subsp. vulgaris)-trials in Lower Saxony. *Julius-Kühn-Archiv*, *464*, 270–279.

Wätzold, F., Jauker, F., Komainda, M., Schöttker, O., Horn, J., Sturm, A., & Isselstein, J. (2024). Harnessing virtual fencing for more effective and adaptive agri-environment schemes to conserve grassland biodiversity. *Biological Conservation*, *297*(110736), 110736.

Weltin, M., & Hüttel, S. (2023). Sustainable intensification farming as an enabler for farm Eco-efficiency? *Environmental & Resource Economics*, *84*(1), 315–342.

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. *Agricultural Systems*, *153*, 69–80.

Wuepper, D., Wiebecke, I., Meier, L., Vogelsanger, S., Bramato, S., Fürholz, A., & Finger, R. (2024). Agri-environmental policies from 1960 to 2022. *Nature Food*, *5*(4), 323–331.

Wunder, S., Börner, J., Ezzine-de-Blas, D., Feder, S., & Pagiola, S. (2020). Payments for environmental services: Past performance and pending potentials. *Annual Review of Resource Economics*, *12*(1), 209–234.

Wunder, S., Engel, S., & Pagiola, S. (2008). Taking stock: A comparative analysis of payments for environmental services programs in developed and developing countries. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *65*(4), 834–852.

Yousaf, A., Kayvanfar, V., Mazzoni, A., & Elomri, A. (2023). Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions. *Frontiers in Sustainable Food Systems*, *6*. https://doi.org/10.3389/fsufs.2022.1053921

Zabel, A., & Roe, B. (2009). Optimal design of pro-conservation incentives. *Ecological Economics: The Journal of the International Society for Ecological Economics*, *69*(1), 126–134.

Zahl-Thanem, A., Burton, R. J. F., & Vik, J. (2021). Should we use email for farm surveys? A comparative study of email and postal survey response rate and non-response bias. *Journal of Rural Studies*, *87*, 352–360.

Zingsheim, M. L., & Döring, T. F. (2024). What weeding robots need to know about ecology. *Agriculture, Ecosystems & Environment*, *364*, 108861.

Chapter 2

Field observation and verbal exchange as different peer effects in farmers' technology adoption decisions*

Abstract. Farmers' adoption of novel technologies is influenced by other farmers' behavior, a phenomenon known as peer effects. Although such effects have been studied intensively, the literature does not clearly distinguish between those that result 1) from verbal exchanges with other farmers and 2) from field observations, including the application of technology, its outcomes, and field conditions. We extend existing theoretical concepts and hypothesize that verbal information exchanges and field observations are two types of peer effects. Using data from an online survey of German sugar beet farmers' application of mechanical weeding from early 2022, we find that the likelihood of adopting mechanical weeding increases across all model specifications by around 26%–28% if at least one adopter is known and by approximately 30%–32% if at least one field is observed. The two types of peer effects complement and reinforce each other in explaining adoption decisions. The effects increase with the number of adopters known and fields observed but decrease with larger distances to the observed fields. The findings can support designing extension services and future peer effects research that should consider the distinction between peer effects arising from verbal exchanges and field observations.

Keywords: *Social Network, Peer Effects, Observability, Spatial Information Diffusion, Technology Adoption, Farm Survey, LASSO Double Selection*

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2.1 Introduction

Peer behavior is an essential driver of farmers' technology adoption decisions (Shang et al., 2021). Exchange with peers could increase farmers' intention to adopt novel sustainable farming practices (Sampson & Perry, 2019), to reduce pesticide usage (Bakker et al., 2021), and can reinforce the effectiveness of advisory services (Genius, Koundouri, Nauges, & Tzouvelekas, 2014). The rich body of literature on the role of peers considers various ways to define "peer effects" covering purely verbal exchange with adopters (Albizua, Bennett, Pascual, & Larocque, 2020) and field observation (Mekonnen et al., 2022). However, existing studies do not consider to what extent these types of peer effects differ. Deeper knowledge of the mechanism that underlies peer effects is important for improving advisory services and policy measures, but missing (Bartkowski & Bartke, 2018; Bramoullé et al., 2020; Brown et al., 2018; Pe'er et al., 2020). So far, the variety of definitions in the current literature makes it difficult to understand the mechanism underlying peer effects: is it through verbal exchange, field observation, or a mix of both?

The research objective of this paper is to disentangle *(verbal) information exchange with adopters* from *observing fields on which a (new) technology is or was used* as two distinct types of peer effects. We are interested in the correlation between the two potential types of peer effects, verbal exchange and field observation, and farmers' technology adoption decisions. Further, we aim to understand how the two types relate to each other. Ideally, we would be able to identify causal effect of verbal exchange and field observations on adoption. However, as outlined in detail below, doing so is conceptually challenging. Nevertheless, studying the correlation between the two types of peer effects (verbal exchange and field observation) and their relation to adoption allows to derive information on their relative importance and difference. To reach our objectives, we structure our analysis along the following research questions:

1. How do (verbal) information exchange and field observation relate to adoption of technology?

2. Do the two types complement each other in explaining the technology adoption decision?
3. How do the two types relate to each other within the relevant socio-spatial network[†]?

We focus on farmers' decision to use mechanical weeding using data from an online survey with sugar beet farmers from early 2022. The German sugar beet production sector is characterized by well-organized advisory structures that deliver information through sugar beet factories, sugar beet associations, and sugar producers to farmers. Current German sugar beet farming depends mainly on herbicides for effective weed control. Herbicide usage is among the main drivers of biodiversity loss in agricultural areas in the European Union (EU) (Gill & Garg, 2014; Petit et al., 2015). The regulatory approval of available active ingredients for herbicide applications is likely to become more limited due to environmental concerns, leading to the need for alternative measures, such as mechanical weeding (EU, 2012; Warnecke-Busch et al., 2020). Novel technologies, such as weeding robots, allow farmers to reduce herbicide usage while maintaining high yields, thereby decreasing agricultural production's negative impacts on biodiversity (Finger, Swinton, et al., 2019). Mechanical weeding has clear ecological benefits, including increased biodiversity abundance compared to chemical weeding, but it can also have adverse effects, such as soil erosion (Liebman et al., 2016; Thiel, Mergenthaler, & Haberlah-Korr, 2021; Ulber, Klimek, Steinmann, Isselstein, & Groth, 2011; Vasileiadis et al., 2017).

The relations between individual's outcomes and those of their peers, known as "peer effects" (Bramoullé, Djebbari, & Fortin, 2009), have received intensive study in the domain of farmers' technology adoption decisions in different geographical and cultural contexts. Bandiera and Rasul (2006) distinguish between social networks based on self-reported individuals versus those based on ex-ante set geographical and cultural proximity. The former are defined as peer effects, either based on purely verbal information exchange (Albizua et al., 2020), take into account whether the adopters are

[†] We define the term "socio-spatial network" as the composition of the number of adopters known, the number of fields observed and the distance to the fields observed.

known (Bandiera & Rasul, 2006; Blasch et al., 2020), or focus on the awareness of other farmers and their fields (Conley & Udry, 2001, 2010; Conley et al., 2003; Mekonnen et al., 2022) to approach field observation. The latter presumes a (more or less clearly defined) mix of verbal and visual information, implicating field observation through spatial proximity. Some empirical studies refer to a certain radius (Di Falco et al., 2020; Kolady et al., 2021; Krishnan & Patnam, 2014; Läpple et al., 2017; Sampson & Perry, 2019) and others to administrative districts, such as villages (Besley & Case, 1993; Foster & Rosenzweig, 1995; Munshi, 2004). However, insight into the mechanism underlying peer effects is limited (Bramoullé et al., 2020), and statistical evidence for the role of farmer-to-farmer interaction in farmers' technology adoption decisions is scarce (Shang et al., 2021). So far as we know, no previous research has explicitly investigated the differences between verbal exchange and field observation as two distinct types of peer effects. We intend to derive a first indication of the importance of and difference between the two types of peer effects that can serve as the basis for future research in this direction.

We find that verbal exchange and field observation both positively relate to the adoption decision, whereby verbal information exchange seems to be relatively slightly more important than field observation in predicting adoption. Hence, personally knowing adopters and verbally exchange information regarding mechanical weeding might play an important role for the adoption decision, besides observing mechanical weeding on other farmers' fields. Despite the high correlation between the two types of peer effects, we are able to estimate separate effects indicating complementarity in explaining the adoption decision. We show that in a relevant socio-spatial network, which is large in terms of number of known adopters and number of fields observed but is small in terms of spatial radius, verbal exchange, and field observation reinforce each other.

With this study, we improve the understanding of the mechanism underlying peer effects by being the first to clearly differentiate between (verbal) information exchange and field observation as distinct types of peer effects. Our empirical investigation contributes to examining the extent to which the two types relate to the adoption decision and how far they complement and reinforce each other. Based on our findings, future research can further explore the mechanism and causal relationships behind these two types of peer effects. Additionally, we present a novel survey tool that allows to capture spatially explicit data on farmers' own fields and the fields they observe, which might also help answer other research questions. Lastly, our findings allow us to derive implications for designing advisory services and policies aiming at reduced herbicide usage or technology adoption. We derive that combining opportunities for verbal exchange with the option to observe a technology and its results in use might prove most efficient in steering farmers' behavior in a desired direction. While we focus on mechanical weeding, our research can also show how other novel technologies are diffused, such as mechanical weeding robots.

The remainder of our paper is structured as follows. We first derive our hypotheses based on existing literature on peer effects in section 2. In section 3, we describe in detail the development of our survey and explain the methods used, including our empirical strategy of how to deal with Manski's reflection problem (Manski, 1993) in peer effects. We then present and discuss our findings in section 4 and conclude with implications for future research and policy design in section 5.

2.2 Peer effects in technology adoption and derivation of hypotheses

In his theory of diffusion of innovations, Rogers (2003) describes the necessary knowledge of an innovation as created through different sources of information at different stages in the adoption process. Peers are a critical source of information, as they provide relevant, readily available, and low-cost information (McBride & Daberkow, 2003; Noy & Jabbour, 2020; Prokopy et al., 2019; Šūmane et al., 2018) and thereby shape farmers' decision making (Foster & Rosenzweig, 1995; Skaalsveen et al., 2020; Villamayor-Tomas et al., 2021). The relevance of this information could differ depending on who is considered important, such as family members, friends, or other successful farmers (Bessette, Zwickle, et al., 2019; Genius et al., 2014; Mekonnen et al., 2022), if the other is well known (Manson, Jordan, Nelson, & Brummel, 2016) or has deep roots in the community (Noy & Jabbour, 2020).

2.2.1 *Verbal exchange with adopters*

Face-to-face interactions with peers are among farmers' most important sources of information (Skaalsveen et al., 2020). Talking to peers can happen with intent but could also be prone to some bias, either in terms of whom one chooses to speak with (Krishnan & Patnam, 2014) or in terms of the interpretation that the speaker or listener might add (Mekonnen et al., 2022). Through verbal exchange, information about unobservable characteristics of a technology, like costs, expected herbicide reductions, time and labor requirements, or necessary skills, can be obtained (Albizua et al., 2020; Jabbour, Gallandt, Zwickle, Wilson, & Doohan, 2014). Studies of peer effects based on verbal exchange often include the frequency of communication (Conley et al., 2003; Tran-Nam & Tiet, 2022), account for the number of adopters known and the distance to them (Krishnan & Patnam, 2014; Sampson & Perry, 2019), or differentiate between different types of peers talked to (Albizua et al., 2020; Mekonnen et al., 2022). We assume that for verbal exchange, peers can be neighbors in close spatial proximity, as well as other farmers who were met at fairs and on field days and whose opinions are important but who are not nearby.

2.2.2 *Observation of adopters' fields*

Rogers (2003) describes observability as an important characteristic of an innovation. We broaden this definition by explicitly referring to the possibility of observing a technology in use, not only its results. Fields could be observed rather unconsciously, as a farmer might observe a field when passing but without actively thinking of it (McCann et al., 2015) or as a conscious action known as "road-side farming" (Burton, 2004), describing the process of farmers checking out "symbols of good farming" on neighboring farms and fields. In the case of weed management, these symbols can be easily observed, e.g., in terms of tidy, weed-free fields or high yields (Lavoie & Wardropper, 2021). There is empirical evidence that the likelihood of adoption varies depending on whether the technology in use (Blasch et al., 2020), and especially its results can be observed easily (Llewellyn, 2007; McCann et al., 2015). Moreover, local information has been found to be of major importance, as farmers close by might face the same production conditions (Arbuckle et al., 2013; Llewellyn, 2007; Noy & Jabbour, 2020; Šūmane et al., 2018). Mekonnen et al. (2022) found that spatial proximity and knowledge of peers' decisions on the use of agricultural inputs and their outcomes, combined with awareness of their plots, explain information diffusion through peers. However, little statistical evidence on the importance of observability as a relevant attribute of technologies for the adoption and diffusion of digital farming technologies has been published (Shang et al., 2021). We assume that observing the fields where mechanical weeding is performed could be positively correlated with adoption as a technology in use, but in particular, its long-term effects over a full production period can be observed under the same local conditions.

2.2.3 *Endogeneity and reverse causality in peer effects*

We depict our theoretical assumptions in Figure 2.1. As shown by the arrows in both directions, we emphasize the possibility of reverse causality. While most peer effects research focuses on the causal effect of peers' adoption behavior on the adoption decision of the individual farmer, the direction of the effect can also be reverse: Farmers might first adopt a technology and then broaden their social network and engage in information exchange. Examples of such behavior include access to chat groups upon the adoption of a certain app or software (Wims & Byrne, 2015), access to machinery rings upon the adoption of a certain machinery, or access to groups that exchange the experience with a certain farming practice (Chaudhuri, Roy, McDonald, & Emendack, 2021). Further, there is evidence that (early) adopters of technology tend to communicate about it to gain social recognition (Shikuku, Pieters, Bulte, & Läderach, 2019), which shows that information dissemination behavior might change *after* technology adoption.

Another obstacle in identifying peer effects is endogeneity in the network formation process (Bramoullé et al., 2020). Individuals might actively choose their own peer group, leading to selection bias (Blasch et al., 2020; Krishnan & Patnam, 2014; Skaalsveen et al., 2020). Individuals tend to be more willing to connect with others who are similar, a phenomenon known as homophily (McPherson, Smith-Lovin, & Cook, 2001). In our case, farmers who are most interested in mechanical weeding could actively search for information themselves by joining networking events or by engaging a lot with like-minded farmers before and after the adoption.

Lastly, the relationship between verbal exchange and field observation might also be prone to endogeneity, as observing a field might induce talking to the respective farmer and the other way around. While it is difficult to control for reverse causality and endogeneity, we are merely interested in the correlation and do not aim for causal inference. We aim to investigate in how far adoption is associated with peers' adoption and how the two types of peer effects relate to each other, irrespective of the causal direction.

2.2.4 *Hypotheses*

Against this background, we formulate our hypotheses, as also depicted in Figure 2.1.

Hypothesis 1a: *Knowing at least one other farmer doing mechanical weeding is positively related to having adopted mechanical weeding.*

Hypothesis 1b: *Observing at least one field where mechanical weeding is done is positively related to having adopted mechanical weeding.*

Hypothesis 2: *Verbal information exchange and field observation as two types of peer effects complement each other in explaining the adoption decision.*

Hypothesis 3: *Verbal information exchange and field observation reinforce each other, such that the correlation with adoption is higher for an increasing number of adopters known, for an increasing number of fields observed, and for a decreasing distance to these fields.*

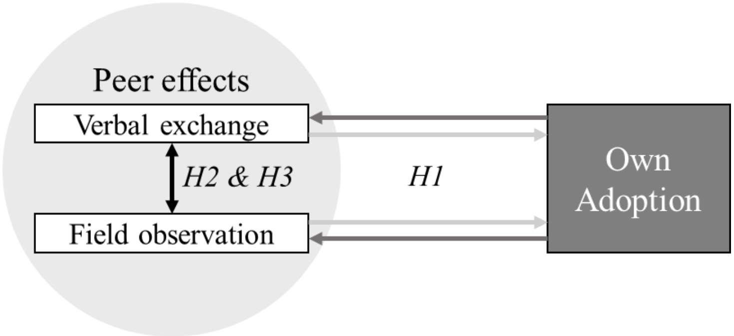

Figure 2.1: Types of peer effects

Source: own presentation

2.3 Method and data

2.3.1 *Survey design and implementation*

To answer our research questions, we conducted an online survey among German sugar beet farmers in early 2022. We designed and implemented a custom-built survey tool, allowing us to obtain explicit spatial data. In this survey, farmers were asked to specify whether, which, and since when they used mechanical weeding techniques. The participants indicated how many other farmers whom they knew used mechanical weeding and were then asked to show on an interactive map where they were growing sugar beets and to indicate fields of other farmers where mechanical weeding is done (whether in sugar beet or other crops). As an alternative for those who did not wish to use the map to provide the precise geolocation of fields, participants were asked to give their postal code and select via a single-choice question how many fields they knew of where mechanical weeding is done. For those who did not use mechanical weeding, we asked for the reason for this. All of the participants were asked about their intention to use new weeding technologies in upcoming years. For the map shown in the survey, we used freely available geo-data on field shapes for certain federal states of Germany, as well as remote sensing data from Copernicus for the remaining federal states (for more information, see the original survey in the Appendix). Using this, participants could select their own or others' fields, either by clicking on the fields or by setting a marker (tractor symbol) (Figure 2.2).

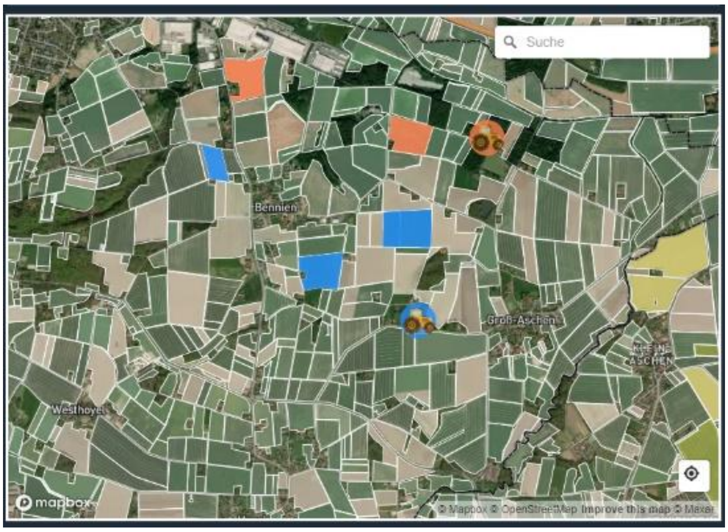

Figure 2.2: Novel custom-build survey tool

Note: Orange areas indicate own fields, and blue areas indicate other farmers' fields where mechanical weeding was observed (example)

2.3.2 *Preregistration & sampling strategy*

We pre-registered this study using the Open Science Framework (OSF) platform on February 10, 2022, the day we began the data collection (Massfeller & Storm, 2022). In this preregistration, we described our study plan, including research questions and hypotheses, study design and sampling strategy, and the variables and models used for the analysis (more information on the preregistration, including how and why we deviated from it, can be found in the Appendix). We relied on a convenience sample, as we published advertisements off- and online, as well as cooperated with the advisory network of the German sugar beet industry, the Institute for sugar beet research (IFZ), and a market research company. In the preregistration, we present an a priori power analysis and describe how we would deal with a potentially biased sample. The code used for the analysis can be found on the author's GitHub page[‡].

2.3.3 *Empirical approach*

Reflection problem and potential biases

The identification of peer effects is challenging, as an individual's and peers' behavior may correlate for several reasons (Di Falco et al., 2020; Krishnan & Patnam, 2014; Manski, 1993). Manski (1993) differentiates between three possible effects:

a) endogenous effects, wherein the propensity of an individual to behave in some way varies with the behavior of the group; additionally, the behavior of the group could be impacted by the behavior of the individual,

b) exogenous (contextual) effects, wherein the propensity of an individual to behave in some way varies with the exogenous characteristics of the group; and

c) correlated effects, in which individuals in a given group tend to behave similarly because they have similar individual characteristics or face similar institutional environments.

While we are interested in the endogenous effects, i.e., the correlation between the peers' and the own adoption decision through field observation and/or knowing adopters, we assume that to address our research question, the differentiation between social (that is endogenous and exogenous effects) and correlated effects is the main necessary and sufficient point. The main challenge is to prevent bias from correlated effects. In the following, we describe how not controlling for correlated and (to a lesser extent) exogenous effects would lead to an overestimation of social effects and how we try to limit such distortion.

Examples of correlated effects are similar natural production conditions (soil quality, topography, etc.) as they could favor or disfavor mechanical

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[‡] AnnaMassfeller/SugarbeetSurveyAnalysis (github.com)

weeding, shared advisory services that communicate a certain attitude toward different weed management decisions, contractors that offer a specific type of machinery, or demonstration farms that support certain farming practices. Further, social norms, such as environmental concerns among the wider community, could lead to correlated effects if farmers' behavior differs in response to these concerns. These effects can lead to a correlation between an individual's and peers' adoption. Not controlling for these correlated effects risks overestimating peer effects.

A possible example of exogenous effects based on peers' characteristics could be the peers' experience with the technology or access to machines, e.g., depending on the structure of the peers' farms and its specialization, machinery might still be available but not in use, making it free for borrowing. Here, even if neighbors (currently) do not use the technology, they can impact adoption by lending the relevant technology. As we are merely interested in the correlation between verbal exchange and field observation as two types of peer effects and adoption, to provide a first indication of their relative importance and difference, the main challenge is to reduce bias from potentially correlated effects and to isolate the social (endogenous and exogenous) effects.

In our model, information on other adopters (*KnowAdopters)* is used to approximate the possibility of (verbal) information exchange with adopters. Similarly, the knowledge of mechanically weeded fields from others (*ObserveFields*) provides information on the awareness of other fields (see formulation of relevant questions for *KnowAdopters* and *ObserveFields* in the original survey in the Appendix). Both variables are coded in our model as binary variables with 1 if other adopters are known / fields are observed, respectively, and 0 if not. We denote farmer *i*'s indication to adopt mechanical weeding by *Adopt*, modelled as a binary decision, taking 1 if mechanical weeding is applied and 0 if not. We include a vector of control variables *Control* containing farmers' characteristics such as age (1 if > 45 years), farm size (1 if > 50 ha), and, to approach environmental attitude, previous participation in AES (1 if yes) as binary dummy variables. Additionally, to account for the possible correlated effects, we include 1) the minimal distance to demonstration farms (also squared) as a continuous variable. This reflects the minimal distance of the farm *i* to a farm belonging to the network of demonstration farms for organic agriculture that are found all over Germany.[§] We include affiliation with one of the 19 German sugar factories as a dummy variable in *Control*. Thereby, we can account for regional differences as well as for the effect of farm advisors. To do this, we calculate the distance for each farm *i* to each of the German sugar factories and assume that farm *i* delivers to the closest factory. There are 19 sugar factories in Germany, belonging to four sugar producers. We aggregated the factories into 13 groups to avoid very small dummy groups (Figure 2.8 in the Appendix). We proxy potential exogenous effects by including farm-demographic data at the county level, such as average farm size per county (DESTATIS, 2022a). As it was found that larger farms tend to be more likely to adopt novel technologies (Shang et al., 2021), we assume that farm size is a good approximation for peers' experience with technology or access to machinery. We further include a large number of soil- and topography-related variables at the county level that allow controlling for possible exogenous and correlated effects, as noted above. All variables included in the model are presented in Table 2.1.

Table 2.1: List of variables in the model specifications

	Name	Label	Values	Mean
Dependent variable	Adopt	Adoption mechanical weeding binary	'0' '1'	
As in pre-registration[**]	ObserveFields	observing fields binary	'0' '1'	
	KnowAdopters	knowing adopters binary	'0' '1'	
	MinDist_demo	minimal distance to demonstration farm	Num: 0.44 to 70.76	21.25
	Farmsize	farm size in ha over 50 binary		
	AES	participation in AES binary	'0' '1'	
	Age	farmer age over 45 binary	'0' '1'	
	FactoryLocation_agg	sugar factory location aggregated, dummy	19 locations as in Figure 2.8 in the Appendix, aggregated to 13	

[§] More information and a map can be found here: https://www.oekolandbau.de/bio-im-alltag/bio-erleben/demonstrationsbetriebe-oekologischer-landbau/

[**] This deviates from the preregistration as described in the Appendix.

Instrumental variables††	ShareOrgFarms	Share of organic farms in all farms at county level	Num: 0 to 0.32	0.06
	ShareOrgArea	Share of organic area in UAA at county level	Num: 0 to 0.36	0.05
Additional variables in *Control*	Farm_organic	farm organic binary	'0' '1'	
	Mainly_crop	farm specialized in arable farming binary	'0' '1'	
	MeanFarmSize	mean farm size at county level in ha	Num: 18.20–336.5	59.87
	Populationdensity	habitants per sq.km at county level	Num: 36–3077	237.62
	FarmDens	farms per sq.km at county level	Num: 0.16–1.99	1.07
	AreaDens	UAA per total county area in ha	Num: 0.14–0.71	0.51
	ShareSmallFarms	share of small farms (< 10ha) in all farms at county level	Num: 0.06–0.53	0.22
	ShareSmallArea	share of area of farms with <10 ha in total UAA	Num: 273.08–23355.4	1041.8
	Elevation_in_m_mean	mean elevation at county or field level‡‡	Num: 12–533.4	252.98
	Sand_content_percent_mean	mean sand content in soil at county or field level, in %	Num: 0.54–82.06	28.68
	Clay_content_percent_mean	mean clay content in soil at county or field level, in %	Num: 5.44–35.61	20.95
	Slope_in_degrees_mean	mean slope at county or field level, in %	Num: 0.11–13.54	2.6
	ShareArableUAA	share of arable area in total UAA in ha	Num: 31.76–100.6	80.53
	ShareArableInTotalArea	share of arable area in total county area in ha	Num: 8.14–67.6	41.74
Alternative to "factory location"	Association_agg	producer associations aggregated, dummy	10 associations as in Figure 2.8 in the Appendix	

†† Part of *Control*

‡‡ If the geo-coordinates of the fields are available, soil-related variables are included at field level, for all others, the county mean is taken

LASSO double selection

Due to the large number of control variables in a quite small sample, there is a certain danger that parameter estimates exhibit very high variance and hence could not be trusted. Therefore, we need to reduce dimensionality through variable selection (Labovitz, 1965). Instead of selecting variables based on literature or experience, we follow the state-of-the-art (Storm et al., 2019) and opted for the Least Absolute Shrinkage and Selection Operator (LASSO) (Finch & Hernandez Finch, 2016) and apply a double selection approach based on Belloni et al. (2014)[§§]. Initially developed for prediction purposes, the machine learning tool allows one to consider many explanatory variables in different functional forms and then use the data to identify the ones with the most explanatory power.

However, as we're interested in the correlation between our variables of interest, *KnowAdopters* and *ObserveFields*, and the adoption decision, we need to apply the double selection procedure (Alexandre Belloni et al., 2014), to avoid the variables being dropped if they're highly correlated to the variables of interest. For example, variables included to capture exogenous effects, e.g., farm-demographic structures, might also be correlated with our variables of interest, *KnowAdopters* and *ObserveFields*. In a classical LASSO application, these variables would not be selected, as their explanatory contributions are indirectly captured in *KnowAdopters* and *ObserveFields*. In other words, we need to account for the relationship between our variables of interest and the other control variables. Not selecting those variables explaining our variables of interest might lead to omitted variable bias, and the effect of those variables will be incorrectly attributed to the variables of interest. The same could happen the other way around when only variables are selected with a large effect on our variables of interest but a small effect on the outcome.

Therefore, we follow Belloni et al. (2014) and apply a double-selection procedure. The idea is to select variables that are relevant for both the key

[§§] We tried two other empirical approaches, a simple model that we also preregistered and an instrumental variable approach. However, both approaches exhibit limitations as explained in the Appendix and therefore we decided for the LASSO double selection procedure.

variables of interest and the outcome. The union of these sets of selected variables is then regressed on the outcome. The LASSO double selection still relies on the assumption that we have no unobserved confounders (i.e., that all relevant variables are captured in our vector of control variables *Control*). We note that this is a strong assumption and come back to it in the limitations.

We are interested in estimating β_1 and β_2 as depicted in the following base LASSO model (LM_{base}):

$$Adopt_i = \beta_0 + \beta_1 KnowAdopters_i + \beta_2 ObserveFields_i + \boldsymbol{\delta_i} Control_{Adopt} + \zeta_i \tag{1}$$

where E [ζ_i| $Info_i$, $ObserveFields_i$, $Control_{Adopt,i}$, $r_{Adopt,i}$] = 0, $\boldsymbol{\delta_i}$ is a p-dimensional vector unknown coefficients for the p controls where p ≫ n is allowed but not met in our case, and the parameters of interest are β_1 and β_2, with the effect of *KnowAdopter*s and *ObserveField*s on *Adopt.*

In the first step of the double-selection procedure, we run three LASSO models for *Adopt* (LM_1), *KnowAdopter*s (LM_2), and *ObserveField*s (LM_3) as dependent variable, respectively, each time regressed on a vector of control variables *ControlExogenous*$_{Adopt}$, *ControlExogenous*$_{KnowAdopters}$, and *ControlExogenous*$_{ObserveFields}$, always excluding the particular dependent variable. We use the R package *glmnet* which allows us to use LASSO for binary response variables via maximum likelihood estimation (Friedman, Hastie, & Tibshirani, 2010; Simon, Friedman, Hastie, & Tibshirani, 2011).

LM1: $$Adopt_i = \boldsymbol{\delta_i} ControlExogenous_{Adopt,i} + r_{Adopt,i} + \varsigma_i \tag{2}$$

LM2: $$Info_i = \boldsymbol{\delta_i} ControlExogenous_{KnowAdopters,i} + r_{KnowAdopters,i} + v_i \tag{3}$$

LM3: $$Field_i = \boldsymbol{\delta_i} ControlExogenous_{ObserveFields,i} + r_{ObserveFields,i} + u_i \tag{4}$$

with E[ς_i| $ControlExogenous_{Adopt,i}$, $r_{Adopt,i}$] = 0 ,
E[v_i|$ControlExogenous_{KnowAdopters,i}$, $r_{KnowAdopters,i}$] = 0 and
E[u_i|$ControlExogenous_{ObserveFields,i}$,$r_{ObserveFields,i}$] = 0.

We identify the variables that have been chosen in this first step for the three different models (see Table 2.4 in the Appendix). We focus on the variables chosen for the case where the misclassification error is lowest, i.e., Lambda.min.

In the second step, we use maximum likelihood to regress *Adopt* on the union of all variables selected for LM_1, LM_2, and LM_3 named $Controls_{LM1}$, $Controls_{LM2}$, and $Controls_{LM3}$, respectively, leading to the following final LASSO double-selection model LM_{final}:

$$\begin{aligned} Adopt_i &= \\ &\boldsymbol{\delta_i}(\beta_1 Control_{LM1} + \beta_2 Control_{LM2} + Control_{LM3}) \\ &\qquad + \left(\beta_1 r_{KnowAdopters,i} + \beta_2 r_{ObserveFields,i} \right. \\ &\qquad \left. + \ r_{Adopt,i}\right) + (\beta_1 v_i + \beta_2 u_i + \varsigma_i) \\ &= \boldsymbol{\delta_i}\pi + r_{ci} + \eta_i \end{aligned} \tag{5}$$

where E[η_i | $\boldsymbol{\delta_i}$, r_{ci}] = 0 and r_{ci} is a composite approximation error.

Do the two types complement each other in explaining the adoption decision?

To identify whether the two types complement each other in terms of explaining the adoption decision (H2), we look at the explanatory contribution of the variables we use to construct (verbal) information exchange and field observation. This is done to identify how the percentage of correct predictions of the adoption decision (prediction accuracy) varies in relation to whether the variables for only one or both types of peer effects are included. If the inclusion of variables for both types of peer effects increases prediction accuracy, we can conclude that different aspects can be explained by their means, indicating complementarity. For this, we compare predication accuracy between different models in which the dependent variable is always the adoption decision and a vector of control variables is included as in the simple pre-registered model (see Appendix for details on this model). As explanatory variables, the different models include our different constructs measuring field observation a) binary as ObserveFields or b) as number of fields observed (NrFields), with the levels “no fields observed” (reference category), “1–5 fields observed,” “6–10 fields observed," and ">10 fields observed," or c) as distance to fields observed (FieldDist***), with the levels "no fields observed" (reference category), "fields in 0–5 km distance observed," "fields in 6–10 km distance observed," "fields in 11–30 km distance observed," and "fields in >30 km distance observed." Similarly, knowing adopters are measured a) as a binary with KnowAdopters or b) as number of adopters known (NrAdopters), with the levels "no adopters known" (reference category), "1–5 adopters known," "6–10 adopters known," and ">10 adopters known." Each variable is depicted once alone and then also in combination with each other, together with the vector of control variables Control. We compare the results to a model that includes only an intercept (naïve model) and one that includes only the control variables, leading to 14 models overall that we compare (see Table 2.3 in section 4.3).

How do the two types relate to each other within the relevant socio-spatial network?

To determine whether the two types reinforced each other, we examined the predicted likelihood of adoption, given the interaction of *NrFields*, *FieldDist*, and *NrAdopters*. From H3, we expect the likelihood of adoption to be highest where many adopters are known and many fields are observed in close spatial proximity. We also intend to derive the relevant size (*NrAdopters*, *NrFields*) and structure (*FieldDist*) of the network. We take our simple preregistration model (see Appendix for details) and replace the binary variables *KnowAdopters* and *ObserveFields* with interaction terms of the different variables measuring field observation and knowing adopters leading to the following three probit interaction models IM_1, IM_2, and IM_3:

*** We calculated this variable (if not selected directly via single choice question) by taking the mean of the distances between the centroid of the own fields (if chosen via map) or the centroid of the postal code region (if own fields were not chosen via map but only the postal code was given) and the other farmers' fields.

$$\Pr(Adopt_i{=}1|NrAdopters\_agg_i,\ NrFields_i, Control_i, \beta, \boldsymbol{\gamma}) = \Phi(\beta_0 + \beta_1 NrAdopters\_agg_i + \beta_2 NrFields_i + \beta_3 NrAdopters\_agg_i * NrFields_i + \boldsymbol{\gamma} Control_i + \varepsilon_i) \quad (6)$$

$$\Pr(Adopt_i{=}1|NrAdopters\_agg_i,\ FieldDist\_agg_i, Control_i, \beta, \boldsymbol{\gamma}) = \Phi(\beta_0 + \beta_1 NrAdopters\_agg_i + \beta_2 FieldDist\_agg_i + \beta_3 NrAdopters\_agg_i * FieldDist\_agg_i + \boldsymbol{\gamma} Control_i + \varepsilon_i) \quad (7)$$

$$\Pr(Adopt_i{=}1|NrFields_i,\ FieldDist\_agg_i, Control_i, \beta, \boldsymbol{\gamma}) = \Phi(\beta_0 + \beta_1 NrFields_i + \beta_2 FieldDist\_agg_i + \beta_3 NrFields * FieldDist\_agg_i + \boldsymbol{\gamma} Control_i + \varepsilon_i) \quad (8)$$

where Φ denotes the normal cumulative distribution function, β symbols denote scalars, and $\boldsymbol{\gamma}$ is a vector of coefficients to be estimated. We estimate the models in (7), (8), and (9) using maximum likelihood. *NrFields* enters as described in section 3.3.3. To avoid having too many empty and small groups resulting from the interaction terms, we aggregate two levels of the variable *FieldDist*, leading to *FieldDist_agg*, with the following levels: "no fields observed" (reference category), "fields in 0–5 km distance observed," "fields in 6–10 km distance observed," and "fields in >10 km distance observed," as well as also two levels of *NrAdopters*, leading to *NrAdopters_agg* with the following levels: levels "no adopters known" (reference category), "1–5 adopters known" and ">5 adopters known."

2.4 **Results and discussion**

2.4.1 *Descriptive statistics*

Our original sample consisted of 313 farmers. After data cleaning, the sample size was reduced to 294 observations that were usable for the analysis.[†††] Following the power analysis reported in the preregistration, we

[†††]Due to an error at the beginning of the data collection, spatial data were missing for 18 farms. As there was only one farmer delivering to the sugar factory Cosun Beet Company, we excluded this observation from the analysis to avoid distortion.

achieved a power of 0.93.[‡‡‡] The farmers in our sample are mainly specialized in crop production (74%). Compared to the German farming census from 2020 (see Table 2.2), the participants in our sample were slightly younger than the German average, a common observation in online surveys (Zahl-Thanem et al., 2021). The farm sizes are within the range of the German average for farms that specialize in crop production. Histograms for the distribution of age and farm size in the sample can be found in the Appendix, Figures A 2.2 and A 2.3. The small share of organic farms in our sample reflects the small market for organic sugar beets in Germany (Eurostat, 2021). Of 294 farmers, 39% (114) reported using mechanical weeding in their sugar beets, 82% (242) knew other adopters, and 85% (251) observed other farmers' fields.

Table 2.2: Sample statistics and comparison with German farm census data from 2020

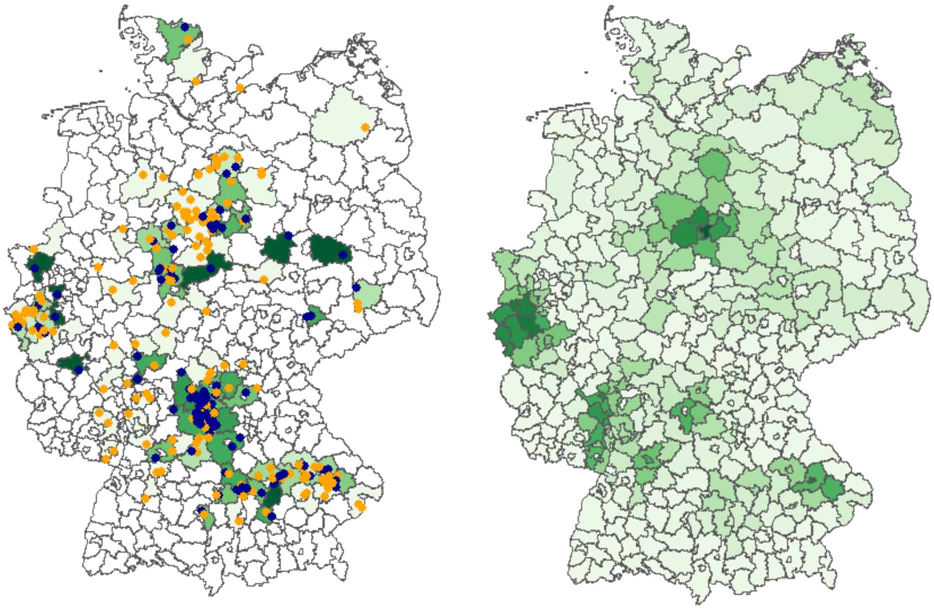
Variable	Whole sample (n = 294) Mode[b] / Mean	Farming census in Germany[a] Mode
Age (in years)	35–44	55–64
Farm size (in ha)	50–99	50–99[c]
Share of organic farms	5%	2.5%[d]
Number of adopters known	1–5	/
Number of fields observed	1–5	/
Distance to fields observed	0–5	/
Minimal distance to demonstration farms (in km)	21.25	/
Mean distance to fields observed (in km)	7.31	/
Mean distance between own fields (in km, n = 232)	3.73	

[a] Bundesministerium für Ernährung und Landwirtschaft (2021)
[b] We asked for all demographic variables in categories to not force participants to reveal too concrete information
[c] Farms with mainly crop production (DESTATIS, 2022a)
[d] Share of organic farms growing sugar beets in all farms growing sugar beets (DESTATIS, 2022b)

The majority of farmers has a rather small and close network, which is in line with earlier findings (Blasch et al., 2020; Conley & Udry, 2010): mostly 1–5 adopters are known, and 1–5 fields are observed at a distance of 0–5 km

[‡‡‡] On the chi-squared test for the contingency tables on *Adopt*, and *KnowAdopters*, and *ObserveFields*, respectively, assuming an effect size w of 0.22 as in Di Falco et al. (2020) and an alpha of 0.05.

(mean: 7.31 km), with a distance between the own fields of 0–1 km (see respective histograms in Appendix Figure 2.21). We find a slight difference between those who selected their own and other farmers' fields via the map tool and those using the single-choice question (more on that in the Appendix). Concerning the spatial coverage, our sample well reflects the pattern of the sugar beet farm structure within Germany (see Figure 2.3).



Sampled farms (yellow = non-adopters, blue = adopters, white = no observations, green = share of adopters per county, the darker the more)

Main sugar beet regions (the higher the share of sugar beet in arable utilized agricultural area per county, the darker the region).

Figure 2.3: Spatial coverage (left) and sugar beet regions in Germany (right)

Most farmers use traditional machinery they own. While previously, the beet hoe was the main tool, machinery has become slightly more diverse in recent years, and also camera/GPS-steered and autonomous machinery is used (see Figure 2.13 in the Appendix). Modern and autonomous machinery is more frequently shared with neighboring farms or used via a machinery ring or contractor service (see Figure 2.14 in the Appendix). The three main reasons that non-adopters gave for not using mechanical weeding are perceived time constraints, perceived low reliability of the technique to efficiently remove all weeds, and high investment costs (see Figure 2.15 in Appendix). Time constraints could relate to the time to actually do the mechanical weeding (on a tractor), but for future technologies, such as robots, supervision time could play a role (Lowenberg-DeBoer, Behrendt, et al., 2021). Hearing of bad experiences from peers or not knowing who to turn to for information on mechanical weeding are among the least important barriers.

2.4.2 *How do (verbal) information exchange and field observation relate to adoption?*

The results from the final LASSO model LM_{final} support our initial Hypothesis 1a: knowing at least one adopter is associated with a 26% statistically significant higher likelihood of adoption, and Hypothesis 1b: observing at least one field where mechanical weeding is associated with a 32% statistically significant higher likelihood of adoption, all else being equal (Figure 2.4). The marginal effects of both variables of interest remain robust in magnitude and significance through all different specifications that underpin trust in our results (see the sensitivity analysis in the Appendix, Figures A 2.8 and A 2.9). We conducted a similar analysis for the intention to adopt, indicating the same direction of effects (see Appendix, Figures A 2.10 and A 2.11).

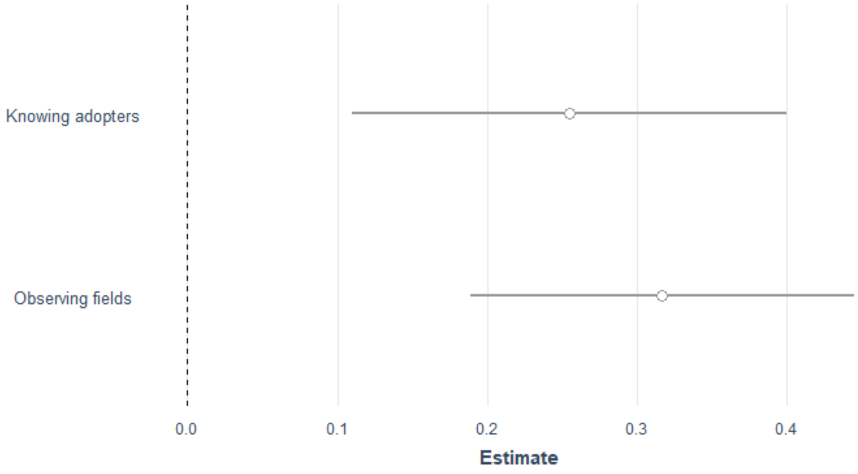


Figure 2.4: Marginal effects for Knowing Adopters and Observing Fields on Adoption of the final LASSO model

Note: Dependent variable = Adoption, Observations: 294; 0.95 confidence intervals are displayed, and partial effects for the average observation are given with standardized standard errors.

Our results on a positive correlation between verbal exchange and field observation and farmers' adoption decisions are in line with similar studies (Mekonnen et al., 2022; Sampson & Perry, 2019). Assuming that a causal relationship underlies the positive correlations between verbal exchange and field observation and farmers' technology adoption decisions, we explain our results by two phenomena: social learning and social pressure. Prior studies highlight the significance of information scarcity and perceived complexity as key obstacles to adopting new farming technologies (Bakker et al., 2021; Foster & Rosenzweig, 1995; Vecchio et al., 2020). Rogers (2003) underscores the pivotal role of perceived complexity in innovation adoption. Social learning, defined as the process of individuals learning from their neighbors' experiences with new technology Rogers (2003), serves as a means to mitigate (perceived) complexity by acquiring relevant information from peers. In our case, social learning could occur as mechanical weeding exhibits a certain complexity in implementation and outcome that might hinder adoption, as costs (e.g., labor time) and effectiveness under different local conditions are difficult to predict (Bessette, Wilson, et al., 2019; Bessette, Zwickle, et al., 2019; Fishkis et al., 2020; Gage & Schwartz-Lazaro, 2019). Information that reduces the perceived complexity of a technology can either be obtained through verbal exchange (Skaalsveen et al., 2020) but also by observing the technology in use and its results (McCann et al., 2015; Skaalsveen et al., 2020). Kolady et al. (2021) trace the effect of observing fields in a certain radius on farmers' adoption decisions back to the reduction in learning costs and the possibility of deriving information on feasibility in the given local setting. We assume that both types of peer effects transmit different information that both reduce the perceived complexity of mechanical weeding and thereby positively relate to the adoption decision.

We propose social pressure as a second mechanism explaining the positive correlation. Rogers (2003) emphasizes social system norms as a precursor to adoption. Déssart et al. (2019), drawing on Cialdini, Reno, and Kallgren (1990), distinguish between descriptive (what other people actually do) and injunctive (what people ought to do) norms and signaling motives (to convey some information about oneself to another party), with evidence suggesting their influence on farmers' technology adoption decisions (Déssart et al., 2019; Shang et al., 2021; Streletskaya et al., 2020; Tandogan & Gedikoglu, 2020). Pagliacci et al. (2020) and Gatto et al. (2019) underscore the role of nearby farmers' behavior in inducing social pressure.

For mechanical weeding, we conjecture that descriptive norms may drive adoption if farmers perceive it as the new "norm," influenced by interactions with many adopters or field observations as individuals have a strong wish to conform with this norm if they find themselves in the minority (Asch, 1956). Recent evidence supports the importance of descriptive norms in farmers adopting organic farming (Tran-Nam and Tiet, 2022). Additionally, we suggest that injunctive norms could also trigger adoption but usually require verbal exchange. Empirical evidence has indicated that injunctive norms play an important role in explaining farmers' adoption decisions (Defrancesco et al., 2007; Kuhfuss et al., 2016; Massfeller et al., 2022; Tran-Nam & Tiet, 2022).

Field observations may play a crucial role in signaling motives, allowing farmers to convey their commitment to fellow farmers and the public. The field's condition serves as a symbol of "good farming" (Burton, 2004). This signaling can involve demonstrating environmental stewardship with weedy, likely biodiversity-rich fields, aligning with findings that environmentally conscious farmers prioritize societal opinions (Defrancesco et al., 2007; Läpple & Kelley, 2013). Alternatively, farmers may seek to showcase "success" with weed-free, high-yielding fields. Notably, weed management practices may affect neighboring fields through spillover (herbicides or weed seeds), creating social pressure for farmers to align their practices with those of nearby farmers (Davis & Carter, 2014; Lavoie & Wardropper, 2021; Macé, Morlon, Munier-Jolain, & Quéré, 2007).

However, as we cannot account for the causal relationship, the reason for the positive relationship between peer effects and adoption could also be based on knowing adopters and observing fields as a *consequence* of the adoption, as farmers might join networking groups to exchange and to visit each other's fields *after* they have adopted, as further discussed in section 4.3. Further, selection bias in terms of individuals actively choosing their own peer group, preferably consisting of similar individuals (McPherson et al., 2001) could explain the positive relationship between peer behavior and own adoption, as found in similar studies (Blasch et al., 2020; Krishnan & Patnam, 2014; Skaalsveen et al., 2020).

2.4.3 *How do the two types of peer effects relate to each other?*

To identify the contribution of individual, distinct variables to explaining the adoption decision, we explore in how far the percentage of correct predictions changes with or without the variable under consideration (see respective coefficient plots in Appendix Figure 2.20). Table 2.3 depicts prediction accuracy (i.e., share of correct predictions) of different model specifications (column 2) and the difference to the model with the highest prediction accuracy in increasing order (column 3). With our best model, we can correctly predict the adoption decision for 77.21% of our sampled farmers compared to 61.22% using a naïve model.

Table 2.3: Prediction accuracy of different models

Model	Prediction accuracy (in %)	Difference from the "best" model (in percentage points)
a) *Naïve*	61.22	15.99
b) *Only Controls*	68.03	9.18
and		
c) *NrFields*	69.39	7.82
d) *ObserveFields*	71.43	5.78
e) *FieldDist* and *NrFields*	71.77	5.44
f) *FieldDist*	72.45	4.76
g) *KnowAdopters*	73.81	3.40
h) *NrAdopters* and *NrFields*	73.81	3.40
i) *KnowAdopters* and *ObserveFields (Pr1)*	74.15	3.06
j) *KnowAdopters* and *NrFields*	74.49	2.72
k) *NrAdopters*	74.83	2.38
l) *NrAdopters* and *ObserveFields*	76.19	1.02
m) *KnowAdopters* and *FieldDist*	77.21	0.00
n) *NrAdopters* and *FieldDist*	77.21	0.00

Our results support our complementarity hypothesis (H2): the variables that we use to construct the two types of peer effects contribute to different extents to explaining the adoption decision. We find that the variables used to depict knowing adopters (*KnowAdopters* and *NrAdopters*, models g and k) exhibit a greater explanatory contribution than those related to field observation (*ObserveFields, NrFields, FieldDist,* models c–f), which could indicate that the former process is more important than the latter. *NrFields* seems to contribute least to an explanation of the adoption decision. A model with only control variables (model b) would predict 68.03% of the choices correctly, which represents a bit more than half of the gain of the full model over the naïve model. If a combination of the different variables describing field observation (*ObserveFields, NrFields, FieldDist*) and knowing adopters (*KnowAdopters, NrAdopters*) is included (Models h,i,j,l,m,n), the prediction accuracy is highest where *FieldDist* is combined with either *KnowAdopters* (Model m) or *NrAdopters* (Model n) and slightly lower where *NrAdopters* is combined with *ObserveFields* (Model l). It seems that once the distance to fields observed is included, the exact number of adopters known (Model n) does not help explain the adoption decision further; it is enough to include if adopters are known or not (Model m). The combination of a variable that describes field observation and one that describes knowing adopters exhibits higher prediction accuracy (Models h,i,j,l,m,n) compared to a model where only the two field variables are included (model e), underpinning the complementarity hypothesis. We explain the finding on complementarity by the different information that might be delivered. While through verbal information exchange, information on unobservable characteristics can be obtained (e.g. costs), field observation allows to get information on the feasibility of the farming practice under the same production conditions over a full production period.

We further find that of the farmers in the sample, 75% observe fields **and** know adopters, and the adoption share is highest in this group. The lowest share of adopters appears among those neither observing fields nor knowing adopters (8% of the sample) (see Figure 2.22 in the Appendix). Then, 7% know adopters but do not observe fields, and 10% observe fields but do not know adopters. This indicates that knowing other farmers and observing fields is highly correlated. Exposure to both types is positively related to a higher likelihood of adoption. Being exposed to only one or none of these types is very rare and comes with a low likelihood of adoption.

To explore the (combined) effects of knowing adopters and observing fields and to derive the relevant size and structure of the network, Figures 2.5, 2.6, and 2.7 present heatmaps of the predicted likelihood of adoption (group size and share of adopters) of the three interaction models (see coefficient plots in Appendix, Figure 2.23) and all possible combinations of the interaction terms, such that the darker the color, the higher the predicted likelihood.

We find that the highest predicted likelihood of adoption is exhibited by those who

1. know many adopters and observe many fields: 90% (Figure 2.5)
2. know many adopters close by: 77% (Figure 2.6)
3. observe many fields close by: 89% and 88% (Figure 2.7)

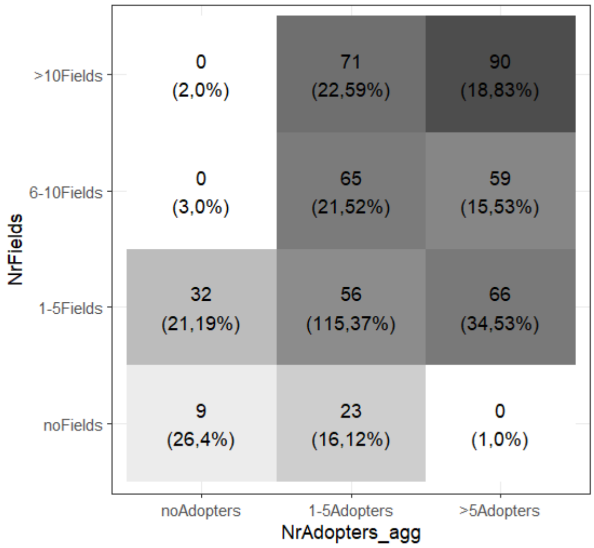


Figure 2.5. Predicted likelihood of adoption (in %) dependent on the interaction between the number of adopters known and number of the fields observed (group size and share of adopters in parentheses)

Note: Own presentation based on own data

These results support our Hypothesis 3, such that the predicted likelihood of adoption correlates positively with the number of adopters known and number of fields observed in close spatial proximity. The two types of peer effects seem to mutually reinforce each other: having a large network among adopters known and many fields observed that are close in terms of spatial radius comes along with a high predicted likelihood of adoption.

Manson et al. (2016) found very similar results for the effect of distance to other farms on the adoption of multifunctional agriculture. Distances below 8 km have a strong impact on the adoption decision, which supports our assumption that local information from farmers and fields facing the same local settings is relevant, likely especially to reduce perceived complexity. This is also reinforced by our finding that the predicted likelihood of adoption increases with the proximity with which a sampled farm is located to a demonstration farm (Appendix Figure 2.27) which was also found in previous research (Wang, Lu, & Capareda, 2020). Our results indicate that knowing many (> 5) adopters comes along with a high predicted likelihood of adoption, especially if many (>10) fields are observed, which is in line with Blasch et al. (2020), Genius et al. (2014), and Bandiera and Rasul (2006), who found the same effect for the likelihood of different types of technology adoption. We presume that descriptive norms might explain these patterns: Knowing many adopters of mechanical weeding and observing many fields where it is being used induce the feeling that most farmers are weeding mechanically, leading to a wish to conform with this (perceived) majority (Asch, 1956). If many (>5) adopters are known (and similarly if many (>10) fields are observed), the predicted likelihood is highest if the fields are observed close by (0–5 km). This strong effect of knowing many adopters close by on the adoption decision has also been seen in similar studies (Genius et al., 2014; Sampson & Perry, 2019).

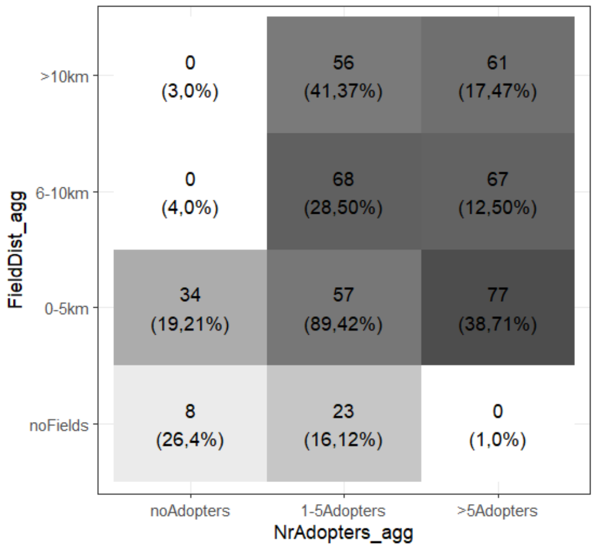


Figure 2.6: Predicted likelihood of adoption (in %) dependent on the interaction between the number of adopters known and distance to fields observed (group size and share of adopters in parentheses)

Note: Own presentation based on own data

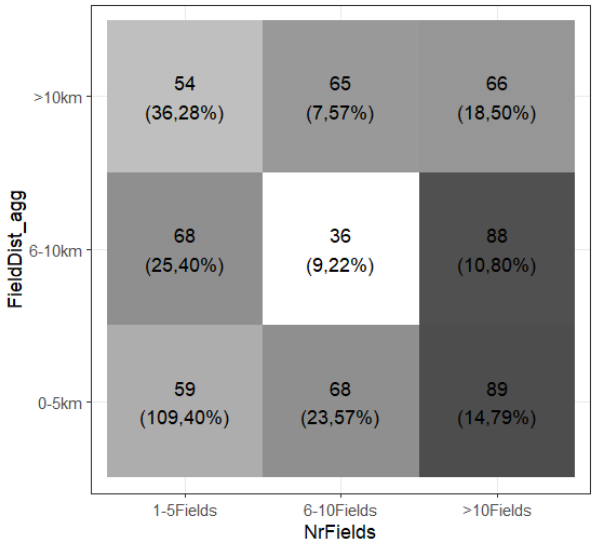


Figure 2.7: Predicted likelihood of adoption (in %) dependent on the interaction between the number of fields observed and distance to fields observed (group size and share of adopters in parentheses)

Note: Own presentation based on own data, Figure 2.7 based on subsample of "observers"

While we cannot tell from our data whether the fields observed belong to known adopters, we find a high correlation between the variables we used to construct *NrAdopters_agg*, *NrFields*, and *FieldDist_agg*, respectively (chi-squared tests $p < 1\%$ for all, see Figures A 2.16–A 2.18 in Appendix). Knowing many (>5) adopters entails observing many (>10) fields further away (>10 km). Unlike the revealed importance of local information from fields nearby, we also see a quite high predicted likelihood for adoption if fields further away are observed, combined with many adopters known (61%) or many fields observed (66%).

In light of these results, we conjecture that endogeneity between the two variables of interest, field observation, and verbal exchange, could be an issue. We cannot rule out that farmers talk to each other more often if their fields are close or that they are more aware of many (close) fields with mechanical weeding if many adopters (= potential respective landowners) are known to them—both observations were made by Mekonnen et al. (2022). In addition, the causal relationship remains unclear; it might simply be that farmers observe a new technology on the field and then approach the farmer to talk about it or that farmers come to know many adopters at a networking event, and after having had a verbal exchange, they visit each other's fields, even further away. Further, throughout our study we rely on the assumption, that the two types of peer effects are based on the same (or highly overlapping) relevant peer group. Nevertheless, both analyses on the relation between verbal exchange and field observation (Table 2.3 and Figures 2.5, 2.6 and 2.7) indicate slightly higher importance of verbal exchange compared to field observation when it comes to the adoption decision. We have to keep in mind, that the results rely on the strong assumption of having no unobserved confounders. However, assuming that such confounders would relate to both types of peer effects to a similar extent, we can still make a statement on the *relative* importance of verbal exchange and field observation.

2.5 **Conclusion**

The theoretical and empirical understanding of peer effects is a crucial factor for steering farmers adoption behavior of novel, sustainable farming technologies in a desired direction. With this study, we contribute to improve this understanding. First, we add to existing theory by differentiating between two types of peer effects, knowing adopters and observing fields. Second, we empirically investigated the roles and relations of these two different types using a novel survey tool developed for this purpose. We have shown that the LASSO double-selection procedure is helpful in terms of including a large number of variables that allow for control for correlated (and to a lesser extent) exogenous effects, even with a relatively small sample size. Using country-level variables to control for correlated or exogenous effects implicitly assumes that the peer network consists only of peers from the same county. This assumption can indeed be questioned; however, as data on additional characteristics is only available at the country level, this is the best possible approach given the available data.

We find that first, the two variables that we used to approximate verbal information exchange through knowing adopters and field observation both exhibit a positive and statistically significant correlation with adoption.

Second, despite the high correlation between the two variables we used to construct our types of peer effects, it remains possible to estimate the correlation of both with adoption indicating a complementary relationship. Third, verbal information exchange seems to be slightly more important in explaining the adoption decision. Finally, the two variables mutually reinforce each other, indicating the importance of a large but spatially close network. The complementary contribution to explaining the adoption decision and the mutual reinforcement of the effects constitute viable findings, even in light of potential endogeneity, reverse causality, and selection bias. Our results provide a clear indication of the importance of differentiating between verbal information exchange and field observation and emphasize the relevance of the *local* production conditions.

Therefore, we advise that future research on farm-level peer effects should distinguish between those arising from verbal exchange and those arising from field observation. Further, the research could test the theoretical assumption of peer effects arising through either social learning and/or social pressure and how the relevance of these two phenomena differs depending on the type of peer effect. In addition, the study of the temporal order of adoption within a certain socio-spatial network could help to identify the causal relationship behind the types of peer effects. We did not account for the relevance of certain peers or groups or if they differ between the two types of peer effects. If our assumption of the two types of peer effects being based on the same (or highly overlapping) relevant peer group is violated, it could impact the relative comparison. Future research could identify the relevant peer groups for each type of peer effect. For example, one could examine whether conventional farmers observe organic fields to understand the usage of mechanical weeding technologies or whether organically farming peers (or their fields) are relevant for either social learning or social pressure, as they might be the first to use novel weeding devices (Shang et al., 2023).

Our results have important policy implications concerning farmers' adoption decisions of new technologies. Based on the finding that verbal exchange seems to be slightly more important for predicting the adoption decision, we derive that advisory services should focus on establishing personal contact between adopters and non-adopters. Given the complementary relationship, field observation possibilities should always be accompanied by the option to verbally exchange, e.g., through field days. Following Reichardt et al. (2009; 2009) and Wang et al. (2020), we suggest that training courses on novel technologies in vocational and technical schools should be combined with practical demonstrations of the new machinery. Policy measures could promote shared ownership of novel technologies, as they seem less likely to be owned alone (Figure 2.14). This would initiate a (verbal) exchange between like-minded farmers, probably accompanied by joint field observations. In addition, policy measures and extension services could be designed more resource-efficiently by offering a technology to certain farmers in a nearby region for experimental purposes, which would allow the necessary field observation and could be accompanied by the possibility of (organized) verbal exchange with (preferably many) adopters.

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Data statement

The data that support the findings of this study are not publicly available due to privacy or ethical restrictions.

2.6 References

Albizua, A., Bennett, E., Pascual, U., & Larocque, G. (2020). The role of the social network structure on the spread of intensive agriculture: an example from Navarre, Spain. *Regional Environmental Change*, *20*(3), 99. doi:10.1007/s10113-020-01676-9

Arbuckle, J. G., Jr, Morton, L. W., & Hobbs, J. (2013). Understanding farmer perspectives on climate change adaptation and mitigation: The roles of trust in sources of climate change beliefs, and perceived risk. *Environment and Behavior, XX*, 1–30.

Asch, S. E. (1956). Studies of independence and conformity: I. A minority of one against a unanimous majority. *Psychological Monographs: General and Applied*, *70*(9), 1–70. doi:10.1037/h0093718

Bakker, L., Sok, J., van der Werf, W., & Bianchi, F. J. J. A. (2021). Kicking the Habit: What Makes and Breaks Farmers' Intentions to Reduce Pesticide Use? *Ecological Economics: The Journal of the International Society for Ecological Economics*, *180*, 106868. doi:10.1016/j.ecolecon.2020.106868

Bandiera, O., & Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal of Nepal*, *116*(514), 869–902. doi:10.1111/j.1468-0297.2006.01115.x

Bartkowski, B., & Bartke, S. (2018). Leverage Points for Governing Agricultural Soils: A Review of Empirical Studies of European Farmers' Decision-Making. *Sustainability: Science Practice and Policy*, *10*(9), 3179. doi:10.3390/su10093179

Belloni, A., Chernozhukov, V., & Hansen, C. (2014). High-Dimensional Methods and Inference on Structural and Treatment Effects. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *28*(2), 29–50. doi:10.1257/jep.28.2.29

Besley, T., & Case, A. (1993). Modeling Technology Adoption in Developing Countries. *The American Economic Review*, *83*(2), 396–402. Retrieved from http://www.jstor.org/stable/2117697

Bessette, D., Wilson, R., Beaudrie, C., & Schroeder, C. (2019). An online decision support tool to evaluate ecological weed management strategies. *Weed Science*, *67*(4), 463–473. doi:10.1017/wsc.2019.21

Bessette, D., Zwickle, S., & Wilson, R. (2019). In the weeds: distinguishing organic farmers who want information about ecological weed management from those who need it. *Renewable Agriculture and Food Systems*, *34*(5), 460–471. doi:10.1017/S1742170518000042

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

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of Econometrics*, *150*(1), 41–55. doi:10.1016/j.jeconom.2008.12.021

Bramoullé, Y., Djebbari, H., & Fortin, B. (2020). Peer Effects in Networks: A Survey. *Annual Review of Economics*, *12*(1), 603–629. doi:10.1146/annurev-economics-020320-033926

Brown, C., Alexander, P., & Rounsevell, M. (2018). Empirical evidence for the diffusion of knowledge in land use change. *Journal of Land Use Science*, *13*(3), 269–283. doi:10.1080/1747423X.2018.1515995

Bundesministerium für Ernährung und Landwirtschaft. (2021). *STATISTISCHES JAHRBUCH ÜBER ERNÄHRUNG, LANDWIRTSCHAFT UND FORSTEN DER BUNDESREPUBLIK DEUTSCHLAND* (No. 65). Retrieved from Bundesministerium für Ernährung und Landwirtschaft website: https://www.bmel-statistik.de/fileadmin/SITE_MASTER/content/Jahrbuch/Agrarstatistisches-Jahrbuch-2021.pdf

Burton, R. J. F. (2004). Seeing Through the “Good Farmer’s” Eyes: Towards Developing an Understanding of the Social Symbolic Value of “Productivist” Behaviour. *Sociologia Ruralis*, *44*(2), 195–215. doi:10.1111/j.1467-9523.2004.00270.x

Chaudhuri, S., Roy, M., McDonald, L. M., & Emendack, Y. (2021). Reflections on farmers’ social networks: a means for sustainable agricultural development? *Environment, Development and Sustainability*, *23*(3), 2973–3008. doi:10.1007/s10668-020-00762-6

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, *58*(6), 1015–1026. doi:10.1037/0022-3514.58.6.1015

Conley, T., & Udry, C. (2001). Social learning through networks: The adoption of new agricultural technologies in Ghana. *American Journal of Agricultural Economics*, *83*(3), 668–673. doi:10.1111/0002-9092.00188

Conley, & Udry. (2010). Learning about a New Technology: Pineapple in Ghana. *The American Economic Review*, *100*(1), 35–69. doi:10.1257/aer.100.1.35

Conley, Udry, C. R., Blume, L., Delav, A., Durlauf, S., Fern, A., … Borde, I. (2003). *Learning About A New Technology: Pineapple in*. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.417.1756

Davis, D., & Carter, J. (2014). Finding common ground in weed management: peri-urban farming, environmental and lifestyle values and practices in southeast Queensland, Australia. *The Geographical Journal*, Vol. 180, pp. 342–352. doi:10.1111/geoj.12034

Defrancesco, E., Gatto, P., Runge, F., & Trestini, S. (2007). Factors affecting farmers? Participation in agri-environmental measures: A northern Italian perspective. *Journal of Agricultural Economics*, *0*(0), 071003055534001-??? doi:10.1111/j.1477-9552.2007.00134.x

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

DESTATIS. (2022a). *Landwirtschaftliche Betriebe, Fläche: Deutschland, Jahre, Bodennutzungsarten, Größenklassen der landwirtschaftlich genutzten Fläche* [Data set]. Retrieved from https://www-genesis.destatis.de/genesis//online?operation=table&code=41141-0002&bypass=true&levelindex=0&levelid=1645623504607#abreadcrumb

DESTATIS. (2022b). *Landwirtschaftszählung: Haupterhebung* [Data set]. Retrieved from https://www-genesis.destatis.de/genesis/online?operation=statistic&levelindex=0&levelid=1687163439069&code=41141#abreadcrumb

Di Falco, S., Doku, A., & Mahajan, A. (2020). Peer effects and the choice of adaptation strategies. *Agricultural Economics* , *51*(1), 17–30. doi:10.1111/agec.12538

EU. (2012, October 26). Consolidated version of the Treaty on the Functioning of the European Union (TFEU, 2007). *Official Journal of the European Union*. Retrieved from https://eur-lex.europa.eu/eli/treaty/tfeu_2012/oj

Eurostat. (2021). Organic crop area by agricultural production methods and crops (from 2012 onwards) (org_cropar) [Data set]. *Organic Crop Area by Agricultural Production Methods and Crops (from 2012 Onwards) (Org_cropar)*.

Finch, W. H., & Hernandez Finch, M. E. (2016). Regularization methods for fitting linear models with small sample sizes: Fitting the lasso estimator using R. *Practical Assessment, Research, and Evaluation*. doi:10.7275/JR3D-CQ04

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

Fishkis, O., Koch, H.-J., & Others. (2020). Risk evaluation of mechanical, chemical and combined mechanical-chemical weed control in sugar beet. *Julius-Kühn-Archiv*, (464), 264–269. Retrieved from https://core.ac.uk/download/pdf/288219883.pdf

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *The Journal of Political Economy*, *103*(6), 1176–1209. doi:10.1086/601447

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software*, *33*(1), 1–22. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/20808728

Gage, K. L., & Schwartz-Lazaro, L. M. (2019). Shifting the Paradigm: An Ecological Systems Approach to Weed Management. *Collection FAO: Agriculture*, *9*(8), 179. doi:10.3390/agriculture9080179

Gatto, P., Mozzato, D., & Defrancesco, E. (2019). Analysing the role of factors affecting farmers' decisions to continue with agri-environmental schemes from a temporal perspective. *Environmental Science & Policy*, *92*, 237–244. doi:10.1016/j.envsci.2018.12.001

Genius, M., Koundouri, P., Nauges, C., & Tzouvelekas, V. (2014). Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects. *American Journal of Agricultural Economics*, *96*(1), 328–344. doi:10.1093/ajae/aat054

Gill, H. K., & Garg, H. (2014). Pesticide: environmental impacts and management strategies. *Pesticides-Toxic Aspects*, *8*, 187. Retrieved from https://books.google.com/books?hl=en&lr=&id=PiShDwAAQBAJ&oi=fnd&pg=PA187&dq=environmental+impacts+of+herbicides&ots=BZnO4-eXTK&sig=t-HxQl_PrkiBaOaf1fXM11n7O-0

Jabbour, R., Gallandt, E. R., Zwickle, S., Wilson, R. S., & Doohan, D. (2014). Organic Farmer Knowledge and Perceptions are Associated with On-Farm Weed Seedbank Densities in Northern New England. *Weed Science*, *62*(2), 338–349. doi:10.1614/WS-D-13-00098.1

Kolady, D., Zhang, W., & Wang, T. (2021). Spatially Mediated Peer Effects in the Adoption of Conservation Agriculture Practices. *Journal of Agricultural*. Retrieved from https://www.cambridge.org/core/journals/journal-of-agricultural-and-applied-economics/article/spatially-mediated-peer-effects-in-the-adoption-of-conservation-agriculture-practices/55A5004D6094FA380E343159B36AD820

Krishnan, P., & Patnam, M. (2014). Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics*, *96*(1), 308–327. doi:10.1093/ajae/aat017

Kuhfuss, L., Préget, R., Thoyer, S., Hanley, N., Le Coent, P., & Désolé, M. (2016). Nudges, Social Norms, and Permanence in Agri-environmental Schemes. *Land Economics*, *92*(4), 641–655. doi:10.3368/le.92.4.641

Labovitz, S. I. (1965). METHODS FOR CONTROL WITH SMALL SAMPLE SIZE. *American Sociological Review*, *30*, 243–249. doi:10.2307/2091568

Läpple, D., Holloway, G., Lacombe, D. J., & O'Donoghue, C. (2017). Sustainable technology adoption: a spatial analysis of the Irish Dairy Sector. *European Review of Agricultural Economics*, *44*(5), 810–835. doi:10.1093/erae/jbx015

Läpple, D., & Kelley, H. (2013). Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers. *Ecological Economics*, Vol. 88, pp. 11–19. doi:10.1016/j.ecolecon.2012.12.025

Lavoie, A., & Wardropper, C. B. (2021). Engagement with conservation tillage shaped by "good farmer" identity. *Agriculture and Human Values*, *38*(4), 975–985. doi:10.1007/s10460-021-10205-1

Liebman, M., Baraibar, B., Buckley, Y., Childs, D., Christensen, S., Cousens, R., … Riemens, M. (2016). Ecologically sustainable weed management: How do we get from proof-of-concept to adoption? *Ecological Applications: A Publication of the Ecological Society of America*, *26*(5), 1352–1369. doi:10.1002/15-0995

Llewellyn, R. S. (2007). Information quality and effectiveness for more rapid adoption decisions by farmers. *Field Crops Research*, *104*(1–3), 148–156. doi:10.1016/j.fcr.2007.03.022

Lowenberg-DeBoer, J., Behrendt, K., Ehlers, M.-H., Dillon, C., Gabriel, A., Huang, I. Y., … Rose, D. (2021). Lessons to be learned in adoption of autonomous equipment for field crops. *Applied Economic Perspectives and Policy*, (aepp.13177). doi:10.1002/aepp.13177

Macé, K., Morlon, P., Munier-Jolain, N., & Quéré, L. (2007). Time scales as a factor in decision-making by French farmers on weed management in annual crops. *Agricultural Systems*, *93*(1), 115–142. doi:10.1016/j.agsy.2006.04.007

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies*, *60*(3), 531. doi:10.2307/2298123

Manson, S. M., Jordan, N. R., Nelson, K. C., & Brummel, R. F. (2016). Modeling the effect of social networks on adoption of multifunctional agriculture. *Environmental Modelling & Software : With Environment Data News*, *75*, 388–401. doi:10.1016/j.envsoft.2014.09.015

Massfeller, A., Meraner, M., Hüttel, S., & Uehleke, R. (2022). Farmers' acceptance of results-based agri-environmental schemes: A German perspective. *Land Use Policy*, *120*, 106281. doi:10.1016/j.landusepol.2022.106281

Massfeller, A., & Storm, H. (2022, February 10). Socio-spatial information sources influencing farmers' decision to use mechanical weeding in sugar beets. doi:10.17605/OSF.IO/QJSBA

McBride, W. D., & Daberkow, S. G. (2003). Information and the adoption of precision farming technologies. *Journal of Agribusiness*, *21*(345-2016–15210), 21–38. Retrieved from https://ageconsearch.umn.edu/record/14671/

McCann, L., Gedikoglu, H., Broz, B., Lory, J., & Massey, R. (2015). Effects of observability and complexity on farmers' adoption of environmental practices. *Journal of Environmental Planning and Management*, *58*(8), 1346–1362. doi:10.1080/09640568.2014.924911

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, *27*(1), 415–444. doi:10.1146/annurev.soc.27.1.415

Mekonnen, D. K., Yimam, S., Arega, T., Matheswaran, K., & Schmitter, P. M. V. (2022). Relatives, neighbors, or friends: Information exchanges among irrigators on new on-farm water management tools. *Agricultural Systems*, *203*, 103492. doi:10.1016/j.agsy.2022.103492

Munshi, K. (2004). Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution. *Journal of*

Development Economics, *73*(1), 185–213. doi:10.1016/j.jdeveco.2003.03.003

Noy, S., & Jabbour, R. (2020). Decision-Making in Local Context: Expertise, Experience, and the Importance of Neighbours in Farmers' Insect Pest Management. *Sociologia Ruralis*, *60*(1), 3–19. doi:10.1111/soru.12267

Pagliacci, F., Defrancesco, E., Mozzato, D., Bortolini, L., Pezzuolo, A., Pirotti, F., … Gatto, P. (2020). Drivers of farmers' adoption and continuation of climate-smart agricultural practices. A study from northeastern Italy. *The Science of the Total Environment*, *710*, 136345. doi:10.1016/j.scitotenv.2019.136345

Pe'er, G., Bonn, A., Bruelheide, H., Dieker, P., Eisenhauer, N., Feindt, P. H., … Lakner, S. (2020). Action needed for the EU Common Agricultural Policy to address sustainability challenges. *People and Nature (Hoboken, N.J.)*, *2*(2), 305–316. doi:10.1002/pan3.10080

Petit, S., Munier-Jolain, N., Bretagnolle, V., Bockstaller, C., Gaba, S., Cordeau, S., … Colbach, N. (2015). Ecological Intensification Through Pesticide Reduction: Weed Control, Weed Biodiversity and Sustainability in Arable Farming. *Environmental Management*, *56*(5), 1078–1090. doi:10.1007/s00267-015-0554-5

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., … Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, *74*(5), 520–534. doi:10.2489/jswc.74.5.520

Reichardt, M., & Jürgens, C. (2009). Adoption and future perspective of precision farming in Germany: results of several surveys among different agricultural target groups. *Precision Agriculture*, *10*(1), 73–94. doi:10.1007/s11119-008-9101-1

Reichardt, M., Jürgens, C., Klöble, U., Hüter, J., & Moser, K. (2009). Dissemination of precision farming in Germany: acceptance, adoption, obstacles, knowledge transfer and training activities. *Precision Agriculture*, *10*(6), 525–545. doi:10.1007/s11119-009-9112-6

Rogers, E. M. (2003). *DIFFUSION OF INNOVATIONS*. Retrieved from https://play.google.com/store/books/details?id=OBhHAAAAMAAJ

Sampson, G. S., & Perry, E. D. (2019). The role of peer effects in natural resource appropriation – the case of groundwater. *American Journal of Agricultural Economics*, *101*(1), 154–171. doi:10.1093/ajae/aay090

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction. *Agricultural Systems, 190*, 103074. doi:10.1016/j.agsy.2021.103074

Shang, L., Pahmeyer, C., Heckelei, T., Rasch, S., & Storm, H. (2023). How much can farmers pay for weeding robots? A Monte Carlo simulation study. *Precision Agriculture*. doi:10.1007/s11119-023-10015-x

Shikuku, K. M., Pieters, J., Bulte, E., & Läderach, P. (2019). Incentives and the diffusion of agricultural knowledge: Experimental evidence from northern Uganda. *American Journal of Agricultural Economics, 101*(4), 1164–1180. doi:10.1093/ajae/aaz010

Simon, N., Friedman, J., Hastie, T., & Tibshirani, R. (2011). Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent. *Journal of Statistical Software*, *39*(5), 1–13. doi:10.18637/jss.v039.i05

Skaalsveen, K., Ingram, J., & Urquhart, J. (2020). The role of farmers' social networks in the implementation of no-till farming practices. *Agricultural Systems*, *181*, 102824. doi:10.1016/j.agsy.2020.102824

Storm, H., Baylis, K., & Heckelei, T. (2019). Machine learning in agricultural and applied economics. *European Review of Agricultural Economics*, *47*(3), 849–892. doi:10.1093/erae/jbz033

Streletskaya, N. A., Bell, S. D., Kecinski, M., Li, T., Banerjee, S., Palm-Forster, L. H., & Pannell, D. (2020). Agricultural adoption and behavioral economics: Bridging the gap. *Applied Economic Perspectives and Policy*. doi:10.1002/aepp.13006

Šūmane, S., Kunda, I., Knickel, K., Strauss, A., Tisenkopfs, T., Des Rios, I. I., … Ashkenazy, A. (2018). Local and farmers' knowledge matters! How integrating informal and formal knowledge enhances sustainable and resilient agriculture. *Journal of Rural Studies*, *59*, 232–241. doi:10.1016/j.jrurstud.2017.01.020

Tandogan, N. S., & Gedikoglu, H. (2020). Socio-Economic Dimensions of Adoption of Conservation Practices: What Is Needed to Be Done? In S. K. Das (Ed.), *Organic Agriculture*. doi:10.5772/intechopen.93198

Thiel, L., Mergenthaler, M., & Haberlah-Korr, V. (2021). Wahrgenommene Umsetzung des integrierten Pflanzenschutzes bei landwirtschaftlichen Betrieben in Nordwestdeutschland. *Gesunde Pflanzen*. doi:10.1007/s10343-021-00548-4

Tran-Nam, Q., & Tiet, T. (2022). The role of peer influence and norms in organic farming adoption: Accounting for farmers' heterogeneity. *Journal of Environmental Management*, *320*, 115909. doi:10.1016/j.jenvman.2022.115909

Ulber, L., Klimek, S., Steinmann, H.-H., Isselstein, J., & Groth, M. (2011). Implementing and evaluating the effectiveness of a payment scheme for environmental services from agricultural land. *Environmental Conservation*, *38*(4), 464–472. Retrieved from http://www.jstor.org/stable/44519302

Vasileiadis, V. P., Dachbrodt-Saaydeh, S., Kudsk, P., Colnenne-David, C., Leprince, F., Holb, I. J., … Sattin, M. (2017). Sustainability of European winter wheat- and maize-based cropping systems: Economic, environmental and social ex-post assessment of conventional and IPM-based systems. *Crop Protection* , *97*, 60–69. doi:10.1016/j.cropro.2016.11.002

Vecchio, Y., Agnusdei, G. P., Miglietta, P. P., & Capitanio, F. (2020). Adoption of Precision Farming Tools: The Case of Italian Farmers. *International Journal of Environmental Research and Public Health*, *17*(3). doi:10.3390/ijerph17030869

Villamayor-Tomas, S., Sagebiel, J., Rommel, J., & Olschewski, R. (2021). Types of collective action problems and farmers' willingness to accept agri-environmental schemes in Switzerland. *Ecosystem Services*, *50*(101304), 101304. doi:10.1016/j.ecoser.2021.101304

Wang, G., Lu, Q., & Capareda, S. C. (2020). Social network and extension service in farmers' agricultural technology adoption efficiency. *PloS One*, *15*(7), e0235927. doi:10.1371/journal.pone.0235927

Warnecke-Busch, G., Mücke, M., & Others. (2020). Mechanical and mechanical-chemical weed control in sugar beets (Beta vulgaris subsp. vulgaris)-trials in Lower Saxony. *Julius-Kühn-Archiv*, (464), 270–279. Retrieved from https://www.cabdirect.org/cabdirect/FullTextPDF/2020/20203252198.pdf

Wims, P., & Byrne, C. (2015). Irish farmers' use of ICTs and their preferences for engagement with extension. *Journal of Extension Systems*, *31*(1). doi:10.18765/jes.v31i1.5626

Zahl-Thanem, A., Burton, R. J. F., & Vik, J. (2021). Should we use email for farm surveys? A comparative study of email and postal survey response rate and non-response bias. Journal of Rural Studies, 87, 352–360. doi:10.1016/j.jrurstud.2021.09.029

2.7 Appendix

2.7.1 *A. Survey*

While the original survey was conducted in German, we show the English version in the following:

Weed control in sugar beet – today and tomorrow

"What we lacked when using the new technology is another farmer from the region with experience"

Sugar beet production is increasingly affected by losses of active ingredients in plant protection products. Farmers need alternatives. Here it is often helpful to look at what colleagues in the region are doing.

We at the University of Bonn conduct a short (maximum 10 minutes) online survey on weed control in sugar beet. The aim of the survey is a better understanding of the role of the exchange between colleagues as a source of information for decisions about new farming practices.

As a farmer, you have the opportunity to provide anonymous information online on how to combat weeds. We are not only interested in farmers who already have experience with mechanical weed control. It is equally valuable for us to know why farmers do not use these techniques or whether they plan to use them in the future!

As soon as the first survey results are available, you can see on a map where farmers have already taken part in the survey and compare which weed control techniques are used where in Germany.

As a giveaway there are three vouchers worth €50 for Engelbert Strauss for every 100 participants.

1. <u>Intro</u>

Welcome to our survey for weed control in sugar beet!

It takes maximum 10 minutes to complete the survey.

All results are analyzed anonymously. If you wish, we will send you a summary of the results.

If you want to be informed about the results you can enter your e-mail address after the survey.

When you need help press the ?-symbol and you will receive more information.

The male form chosen in the survey always refers to female, diverse and male persons.

If you have any questions, please contact: [the author].

To open the survey, please accept our data security statement.

→ Display privacy policy

→ Start the survey

2. <u>Survey</u>

Question 1: Do you use mechanical weed control in your sugar beet? This also includes chemically-mechanically combined weed control such as a hoe band sprayer. In this case, the hand hoe does **NOT** count as a mechanical weed control.

(Need help? → You must answer the question in order to proceed)

• Yes

• No

If question 1 = „Yes":

Question 2: Since when do you use the following techniques? [Table with drop-down selection for devices] or add other techniques that are not in the list:

Comment field: _____

(Need help? Please select a machine. Then fill in the appropriate columns in the table. You can add or remove machines that are not part of the list.)

Additional information to the column "Additional equipment": Does the machine have any special equipment? Have you replaced the device with a new one in the past? Is the device autonomous? Did you add something by yourself? Then please use the comment field.

Tool since:	***Extra equipment/ investment/ comment***	***Whose machine do you use?***
Possible devices: • *Harrow* • *Hoe harrow* • *barrow harrow* • *Rotor harrow* • *Coulter hoe* • *Seperating hoe* • *Rolleing hoe* • *Finger hoe* • *Combination hoe-band sprayer* • *Heaping device* • *Hoe brush* • *Rotary hoe* • *Other: ________*	*a) With camera since* *b) With GPS since* *c) New investment* *d) Autonomous driving* *e) Comment* *f) not stated*	• *Own machine* • *Share with neighbors* • *Machine ring* • *Contractors* • *Other*

Question 3: How many farmers who use mechanically or chemically-mechanically combined weed control (not only in sugar beet!) do you know?

This includes not only farmers who are spoken to on a daily basis, but also farmers with whom you can talk over via phone or at trade fairs, at working group meetings, through farming associations and during field visits.

(Need help? → This does not only mean sugar beet. In this case, the hand hoe does NOT count as a mechanical weed control)

- 0
- 1-5
- 6-10
- more than 10

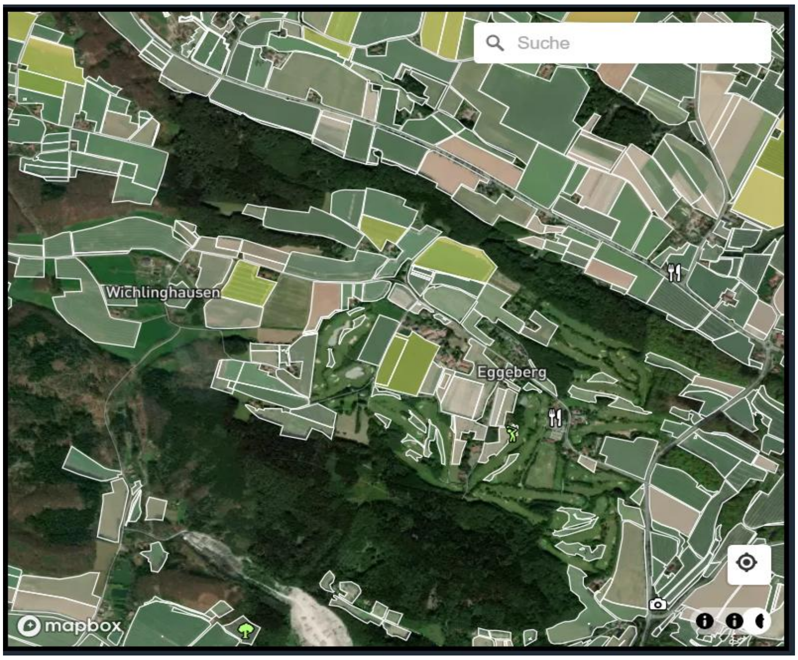
Question 4: In which fields did you grow sugar beet in the last harvest year (2021)? Please click on the appropriate fields or set the marker.

To make it easier for you to choose, we show the field shapes and marked those yellow where we know that there have been cultivated sugar beets fields in the last three marketing years (2019-2021). You can also mark unshaped areas (mainly in Hamburg and Saarland) with the help of a small tractor symbol.

We have taken the data from the Invekos database in the form of so-called shape-files for North Rhine-Westphalia, Lower Saxony and Brandenburg. These data are freely available within the Data License Germany, as specified in the EU INSPIRE Directive. The data for the other federal states is based on remote sensing data (automatically detected field shapes from own calculations based on satellite images taken by Copernicus).

Differences between the shapes of the fields and your actual fields are possible. In this case, simply select the most suitable plot (s). The shape only becomes visible when you zoom in on the map. Information about the fields is of great importance for our analysis, but if you prefer not to click on areas, you can skip this question and alternatively enter your postcode in the next step.

(Need help? → Please mark the appropriate location on the map. You can move the map by holding down the left mouse button. For our evaluation, it is useful to have an indication as precise as possible. You can search for places in the search field in the upper right corner.)



If question 4 is skipped:

Question 4: Please enter your postcode

__________ [numeric input, 5-digit number]

(Need help? → This information is stored anonymously and it is not possible to draw conclusions about individual farms. All data will be aggregated and summarized on the map as at the beginning.)

In both cases, it continues as follows:

Question 5: Do you know fields (e.g. through passing by) on which mechanical or chemical-mechanical combined weed control was applied in the last harvest year (2021)? <u>This does not only include sugar beet fields!</u>

In our analysis, we evaluate the data with regard to the distances between our own fields and other fields. No evaluation of individual farms or fields is carried out. For us, it is interesting how the fields of other farmers, on which you have seen mechanical weed control, are geographically distributed, but not to which farm they belong.

If you don't want to mark the fields or can 't exactly state where the areas are, you can skip this question and enter an approximate number and distance in the next step.

(Need help? → Move the map by holding down the left mouse pointer.)

If question 5 is skipped:

Question 5:

a) How many fields do you know where weeds are removed mechanically or chemically-mechanically combined?

- 0
- 1-5
- 6 – 10
- 11-15
- more than 15

b) How far away are these fields located?

- 0 – 5 km
- 6 – 10 km
- 11 – 15 km
- 16 – 20 km
- 21 – 30 km
- more than 30 km
- I don’t know any fields

(Need help? → Please specify where and how many fields you are aware off while driving by.)

Almost done! You have successfully completed the first part of the survey and your previous answers have been saved. Now we continue with the second part.

In both cases, the second part continues as follows:

Question 6: Can you imagine using mechanical weed control in the future?

Evaluate the following techniques with regard to the 5 statements. Select the statement (s) that best fit(s) your current planning.

Conventional machines for mechanical (e.g. harrow, hoe) or chemically-mechanical combined (e.g. hoe-band sprayer) weed control (without GPS/camera control)	**GPS-guided/camera-controlled machines for mechanical/chemical-mechanical combined weed control (non-autonomous)**	**GPS/camera-controlled autonomous machines for mechanically/chemically-mechanically combined weed control (e.g. robots)**
I am not planning anything I think about getting more information and follow current discussions and literature I am actively seeking for offers and I want to take part	I am not planning anything I think about gaining more information and follow current discussions and literature I am actively seeking for offers and I want to take part	I am not planning anything I think about gaining more information and follow current discussions and literature I am actively seeking for offers and I want to take part

Conventional machines for mechanical (e.g. harrow, hoe) or chemically-mechanical combined (e.g. hoe-band sprayer) weed control (without GPS/camera control)	**GPS-guided/camera-controlled machines for mechanical/chemical-mechanical combined weed control (non-autonomous)**	**GPS/camera-controlled autonomous machines for mechanically/chemically-mechanically combined weed control (e.g. robots)**
in a consultation within the next 5 years I plan to use this technique within the next 5 years (own investment, contractors, ...) I am already using this technique	in an consultation within the next 5 years I plan to use this technique within the next 5 years (own procurement, contractors, ...) I am already using this technique	in an consultation within the next 5 years I plan to use this technique within the next 5 years (own procurement, contractors, ...) I am already using this technique

Question 7:

a) How old are you?

- 15 -24
- 25-34
- 35 -44
- 45-54
- 55-64
- 65 and more
- no information

(b) What is the size of your farm (in ha)?

- less than 5
- 5-9
- 10-19
- 20-49
- 50-99
- 100 -199
- 200 – 499
- 500 -999
- 1000 and more
- no information

c) How do you manage your farm?

- Conventional
- whole farm organic
- Crop production organic
- other parts organic
- no information

d) What is your farm specialization?

- Primarily crop production
- Primarily livestock farming
- Primarily special crops
- Mixed farm
- no information
- Others/comment

e) Are you taking part in an agri-environmental climate measure (voluntary measure from the 2nd pillar of the CAP) during the current funding period (2021-2027)?

- Yes
- No
- no information

(Need help? → This data is used to record the representation of our survey and like the entire survey it is collected anonymously. The farm size refers to the total agricultural area (ownership and lease))

Question 8: Do you have any questions or comments? Feel free to write down your opinion:

(Need help? → Share your thoughts on this survey and on mechanical weed control.)

____ [Free text]

3. The end

Thank you for taking the time to participate in the survey.

Now you have the opportunity to take part in our lottery. We will randomly give away three vouchers for Engelbert-Strauss with a value of € 50 among 100 participants each. Please enter your e-mail address below. This is stored separately from your data and it is not possible to connect it to your answers. If you wish to receive a summary of the results we will send you the summarized results as soon as the data is analyzed.

Would you like to receive the summary of the results by e-mail?

- Yes
- No

Would you like to take part in the lottery?

- Yes
- No

If one of the previous questions is answered with „Yes“ you can see the following information:

Please enter your name and e-mail address here. This data is stored separately and there is no connection to your answers in the survey.

E-mail address: ___________ [free text]

We will never share your e-mail with third parties.

If you have any questions, please contact: [the author]

If question 1 = „No“:

Question 2: Why do you not use mechanical weed control? Select all reasons that fit for you. You also have the option to enter further reasons or explanations by using the comment field. (multiple choice)

- Excessive running costs
- Excessive investment costs
- Too much time required
- Low reliability in weed control
- High risk of damaging the crop
- Not possible on my farm (e.g. due to soil conditions, field sizes,..)
- I don’t know if the technology works for me
- I don’t trust the application/operation
- My colleagues in the region have had bad experiences and told me about them
- I don’t know any colleagues in my region who could give meadvices
- I want to wait until the technology is more mature
- There is no reason for me to change cultivation

free comment field: _______

(Need help? → Please give us some background information about your decision.)

2.7.2 *B. Information on the pre-registration, where and why we deviated from it*

We described two different ways how our two variables of interest, (verbal) information exchange through knowing other adopters (*KnowAdopters)* and, possibility to make field observation (*ObserveFields)* can enter the models: a) as binary or b) as dummy with multiple categories. To answer research question 1, we opted for a), to answer research question 2 and 3 we choose version b). Unless otherwise specified, we follow the pre-registration. One main deviation from the pre-registration concerns the inclusion of the distance to other farmers' fields as explanatory variable. We exclude this variable from our main model (PR1), because it is not straightforward to deal with observations that do not observe any neighboring fields. However, in later models used to answer research question 2 and 3 we include distance to other farmers' fields as dummy variable setting "non-observers" as reference category. As described in the pre-registration we exclude variables from the vector of control variables that show little variation among participants namely the two variables *Farm_organic* (1 if the farm is organic, 0 if not) and 2) *Farm_specialization* (0 if primarily crop production, 1 if primarily livestock farming, 2 if primarily special crops, 3 if mixed farm and 4 if no information). The LASSO double selection procedure, described in the method section, is not part of the pre-registration but it is added as an alternative approach to identify the causal relationship behind our first research question. This alternative approach is added because the instrumental variable suffers empirically from a weak instrument leading to large uncertainty in the estimated effects. We changed the order and numbering of our hypotheses to ease the comprehensibility of our process and avoid causal language, the formulation of the research questions and hypotheses therefore also changed slightly. We extended the formulation of research question 3, the respective hypothesis and the respective analysis by looking at the effect of the interaction terms.

2.7.3 *C. Structure of the German sugar beet sector*

As an alternative to the variable describing belonging to the sugar beet factors (Factory_agg) we also included dummy variables for the ten German advisory associations (Figure 2.8) a sugar beet farmer belongs (Association_agg) to as the German sugar beet production sector is well organized through the advisory associations and farmers receive relevant local information from them. Still there is a high regional overlap between the associations and the factories which is why we used the two versions as alternatives for each other and as a sensitivity check.

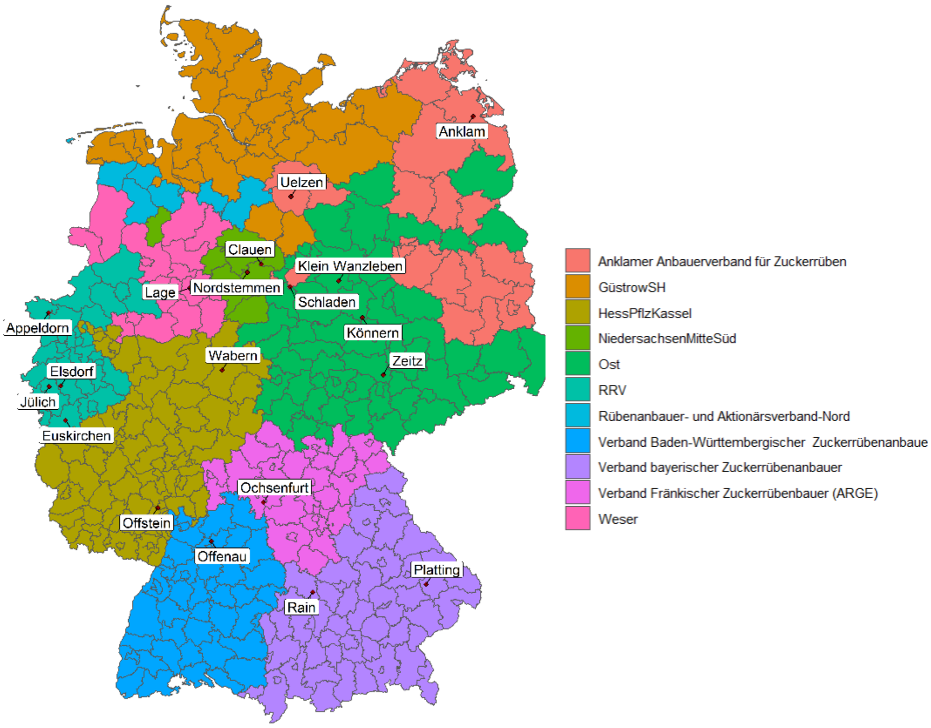


Figure 2.8: Map of sugar beet factories and sugar beet associations

Note: Aggregation of Factory locations: Appeldorn + Euskirchen + Jülich =“West“, Klein Wanzleben + Könnern + Zeitz = „SachsenAnhalt“, Lage + Nordstemmen = „LageNordst“

Source: Data collected from websites of the sugar beet associations and and sugar beet fabrics based on WVZ/ VdZ (2021)

2.7.4. D. First step of the LASSO double selection procedure

Table 2.4: Variables selected in the first step of the LASSO double selection procedure

	Variable	Frequency variable was chosen for the dependent variable: Adoption (LM1)	KnowAdopters (LM2)	ObserveFields (LM3)
As in pre-registration[§§§]	MinDist_demo	49	8	0
	sq.MinDist_demo	0	0	0
	Farmsize	0	0	2
	AES	8	45	2
	Age	18	45	2
	FactoryLocation_agg	13	0	2
Instrumental variables	ShareOrgFarms	0	0	0
	ShareOrgArea	0	19	0
Additional variables in *ControlLasso*	Farm_organic	50	2	0
	Mainly_crop	0	4	0
	MeanFarmSize2	0	0	0
	Populationdensity	0	0	0
	FarmDens	0	45	0
	AreaDens	1	0	2
	ShareSmallFarms	6	45	2
	ShareSmallArea	3	0	2
	Elevation_in_m_mean	0	0	2
	Sand_content_percent_mean	0	45	2
	Clay_content_percent_mean	50	12	0
	Slope_in_degrees_mean	50	0	0
	sq.Elevation_in_m_mean	1	0	1
	sq.Sand_content_percent_mean	0	0	0
	sq.Clay_content_percent_mean	0	45	0
	sq.Slope_in_degrees_mean	0	0	0
	ShareArableUAA	50	0	0
	ShareArableInTotalArea	50	0	0

[§§§] We excluded variables from the pre-registration model as described in the Appendix.

As it can be seen in Table 2.4, the variable describing if the farm is organic or not was selected in all models for *Adoption* as dependent variable which is something that we expected as being an organic farmer requires mechanical weed control. We included the instrumental variables *ShareOrgFarm* and *ShareOrgArea* in the vector of controls (*ControlLasso*) for the first step of the LASSO double selection procedure to verify our initial assumptions on these variables. Especially the exclusion restriction for *ShareOrgArea* is partially supported as this variable is never selected for *Adoption* but 19 times for *KnowAdopters*.

2.7.4 *D. Pre-registration-model*

In our first approach, we isolate social effects by including variables in our model that allow control of correlated effects. We call this the "original preregistration model" (PR1). Information on other adopters (*KnowAdopters)* is used to approximate the possibility of (verbal) information exchange with adopters. Similarly, the knowledge of mechanically weeded fields from others (*ObserveFields*) provides information on the awareness of other fields (see formulation of relevant questions for *KnowAdopters* and *ObserveFields* in the original survey in the Appendix). Both variables are coded in our model PR1 as binary variables with 1 if other adopters are known / fields are observed, respectively, and 0 if not. In addition, we include a vector of control variables *Control* containing farmers' characteristics such as age (1 if > 45 years), farm size (1 if > 50 ha) and, to approach environmental attitude, previous participation in AES (1 if yes) as binary dummy variables (0 if not for all). Additionally, to account for the possible correlated effects, we include 1) the minimal distance to demonstration farms (also squared) as a continuous variable. This reflects the minimal distance of the farm *i* to a farm belonging to the network of demonstration farms for organic agriculture that are found all over Germany.[****] We include affiliation with one of the 19 German sugar factories as a dummy variable in *Control*. Thereby we can account for regional differences as well as for the effect of farm advisors. To do this, we

[****] More information and a map can be found here: https://www.oekolandbau.de/bio-im-alltag/bio-erleben/demonstrationsbetriebe-oekologischer-landbau/

calculate the distance for each farm *i* to each of the German sugar factories and assume that farm *i* delivers to the closest factory. There are 19 sugar factories in Germany, belonging to four sugar producers. We aggregated the factories into 13 groups to avoid very small dummy groups (Figure 2.8). All variables included in the model are presented in Table 2.1. We denote farmer *i*'s indication to adopt mechanical weeding by *Adopt*, modeled as a binary decision, taking 1 if mechanical weeding is applied and 0 if not. We follow a probit specification, and a farmer's probability to adopt mechanical weeding is modeled in model PR1, as follows:

$$\Pr(Adopt_i\text{=}1|KnowAdopters_i,\ ObserveFields_i, Control_i, \beta, \boldsymbol{\gamma})$$

$$= \Phi(\beta_0 + \beta_1 KnowAdopters_i + \beta_2 ObserveFields_i + \boldsymbol{\gamma} Control_i + \varepsilon_i) \qquad (1)$$

where Φ denotes the normal cumulative distribution function, the β symbols denote scalars, and γ is a vector of coefficients to be estimated. We estimate the model in (1) using maximum likelihood. As we only include a few control variables, based on prior knowledge and evidence from the literature, there is a certain risk of omitted variable bias (OVB). We depict the results of PR1 in Figure 2.9.

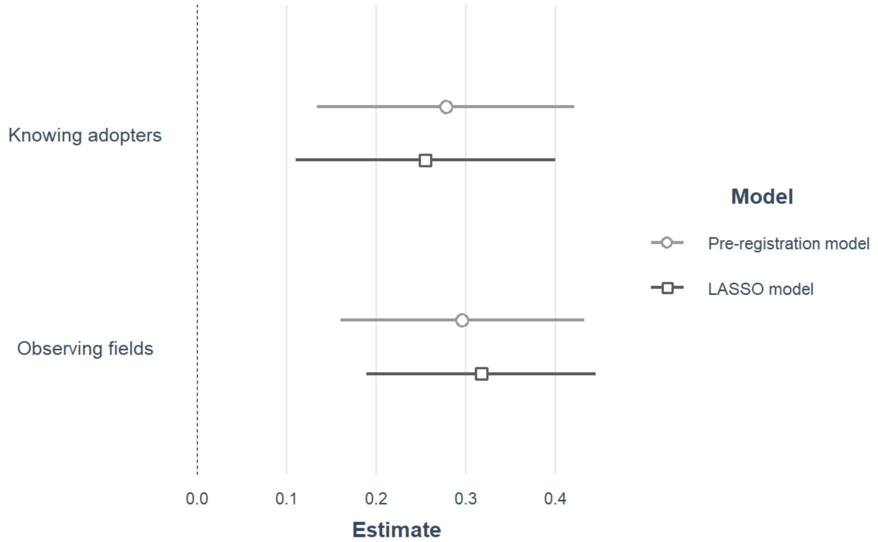


Figure 2.9: Coefficient plot for PR1 results in comparison with LASSO model results

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors

2.7.5 *E. Instrumental variable approach*

Identification strategy 2: Instrumental variables

To overcome the limitations of the simple model PR1, we would ideally use an IV approach that would allow us to isolate the part of the variance in a farmer's adoption decision that can be explained by peers' behavior. In the preregistration, we proposed that organic farming (share of adopters and share of organic area) could serve as a suitable instrument. Organic farmers must do mechanical weeding, independent of environmental conditions or of other farmers. Other famers' behavior influences a farmer's adoption decision only by means of the fact, that they are adopters and that their behavior can be observed or verbally communicated. However, we found that the instrument relevance condition was not sufficiently met: the two IVs are too weakly correlated with the variables of interest *KnowAdopters* and *ObserveFields*. For this reason, the results do not allow meaningful conclusions to be drawn. More details on the IV approach can be found in the Appendix.

We attempt to disentangle endogenous from exogenous and correlated effects by exploring an instrumental strategy using the share of organic farms in the county and share of organic area in the county as instruments similar to Di Falco et al. (2020). Such instrumental variables have to fulfil two requirements (Angrist, Imbens and Rubin 1996; Heckman 1997): they have to be highly correlated with the endogenous variables (instrument relevance condition) but uncorrelated with the error term ν_i (instrument exogeneity condition).

We hypothesize that the share of organic farmers (*ShareFarmOrg*) in a county could serve as instrumental variable for the potentially endogenous variable of knowing other farmers (*KnowAdopters*). Similarly, the share of the organic area (*ShareFieldOrg*) in a county can serve as instrumental variable for the potentially endogenous variable of observing others' fields (*ObserveFields*). For the share of organic farmers and organic area we take German county level data from 2016 (Statistische Ämter des Bundes und der Länder, Deutschland, 2021).

We apply a modified multiple-stage-least-squares approach based on Angrist and Pischke (2009), as "ordinary" 2-Stage-Least-square (2SLS) approaches are less suitable for nonlinear models, like dummy endogenous variables. Therefore Angrist and Pischke (2009) suggest to include another step by using the non-linear fitted values again as instruments, leading to three stages ("3SLS"). Given that we include *KnowAdopters* and *ObserveFields* as dummy variables, we can apply this approach to our case leading to the following model called "IV" (more information on the "3SLS approach" in the pre-registration).

$$\Pr(Adopt_i{=}1|Know\widehat{Adopters}_i, Obser\widehat{veFi}elds_i, Control_i, \beta, \boldsymbol{\gamma})$$

$$= \Phi(\beta_0 + \beta_1 Know\widehat{Adopters}_i + \beta_2 Obser\widehat{ve}Fields_i + \boldsymbol{\gamma} Control_i + \varepsilon_i) \quad \text{(A1)}$$

wherein $Know\widehat{Adopters}_i$ and $Obser\widehat{veF}ields_i$ denote the fitted values arising from the three-stage-least squares approach, Φ denotes the normal cumulative distribution function and the the β's denote scalars and γ a vector of coefficients to be estimated. We estimated the model in (3) using maximum likelihood.

We assume that the instrument relevance condition holds as those farmers who farm organically do mechanical weeding anyway (i.e. *ShareFarmOrg* and *KnowAdopters* are correlated) and that on organic areas mechanical weeding is done anyway, too (i.e. $ShareFieldOrg_i$ and *ObserveFields* are correlated). The instrument exogeneity condition says that the errors should be uncorrelated with the instruments. That should be the case once we account for the number of neighbors known and number of fields aware of (*KnowAdopters* and *ObserveFields*).

Results IV approach

Figure 2.10 shows marginal effects for *KnowAdopters* and *ObserveFields* of our original pre-reg model as well as the marginal effects for the instrumental variable model (IV). We tested for the suitability of the IV by checking for the instrument relevance and instrument exogeneity condition. Concerning the instrument relevance condition, we found via t.test that, there is no significant correlation between the endogenous variable

ObserveFields and the instrumental variables *ShareFarmOrg* and *ShareFieldOrg* (p-values: 0.7288 and 0.9696, respectively).

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors

The relation between *KnowingAdopters* and the two instrumental variables *ShareFarmOrg* and *ShareFieldOrg* is not significant either (p-values: 0.7288and 00.861, respectively). We found a very small negative correlation between both instruments and the error term (both around -0.02), indicating support for the instrument exogeneity condition. Lastly, we could not detect a statistically significant correlation between our outcome variable *Adopt* and the instruments (both p-values > 0.1). We applied the “3SLS” approach as explained in the pre-registration (see Massfeller & Storm, 2022).

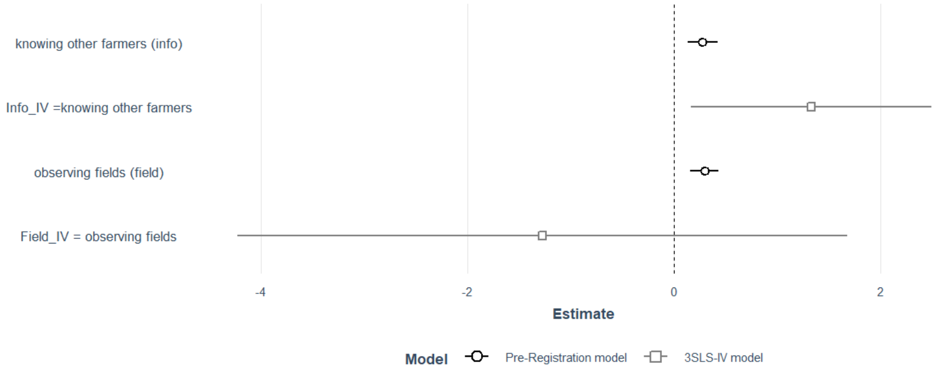


Figure 2.10: Marginal effects for the pre-registration model (PR1) and the IV-Model.

In comparison to the results of the pre-registration model, the results of the 3SLS-model show different effects for both variables of interest. *KnowingAdopters_IV* remains positive and becomes larger, *ObserveFields_IV* turns negative. However, both effects come along with large standard errors. This indicates that the correlation between the instrumental variables and the endogenous variable is too weak to serve as instrument that allows to derive clear conclusions.

2.7.6 *F. Descriptive results & sample characteristics*

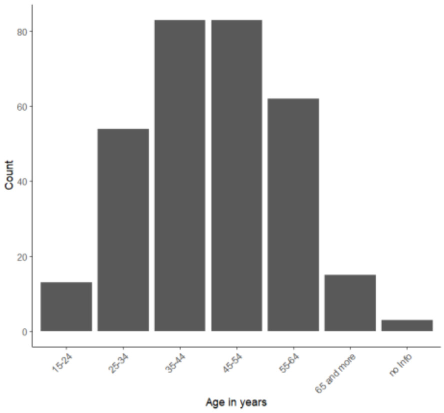


Figure 2.11: Histogram of age distribution of the sample

Source: own survey data

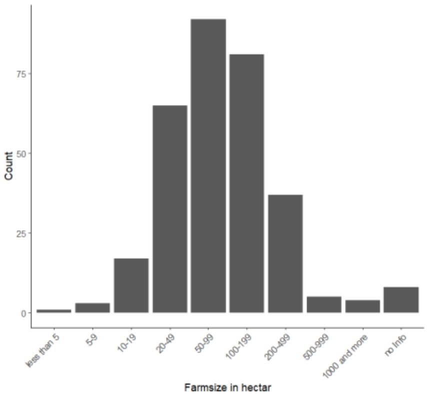


Figure 2.12: Histogram of farm size distribution of the sample

Source: own survey data

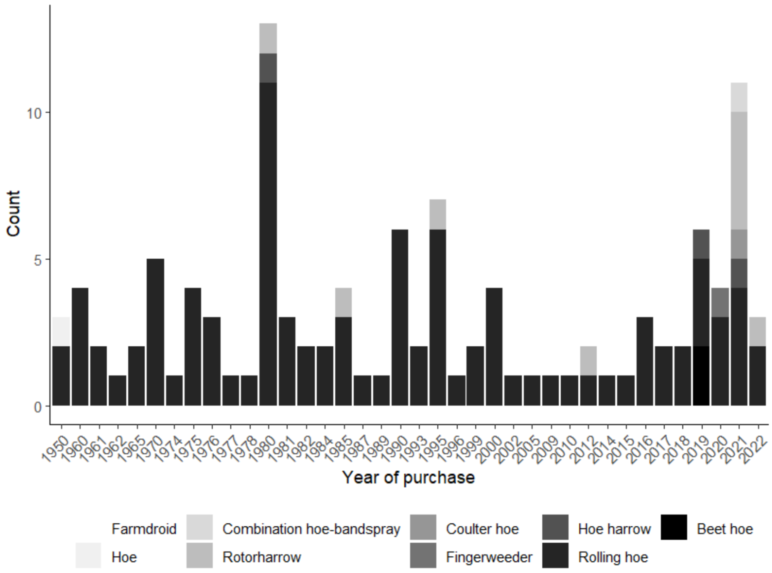


Figure 2.13: Usage of weeding machines over time

Source: own survey data

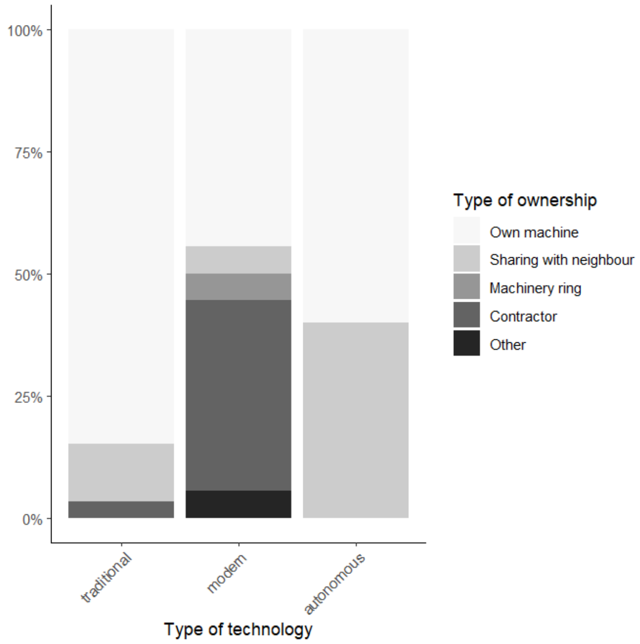


Figure 2.14: Ownership status of used machinery

Source: own survey data

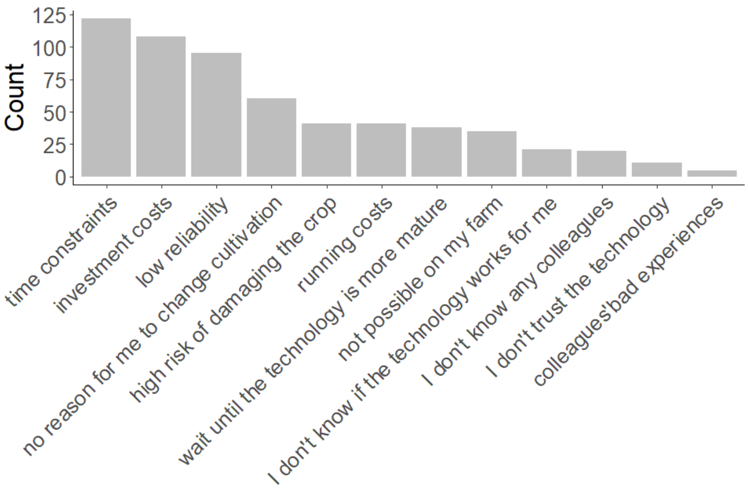


Figure 2.15: Reasons for non-adoption

Source: own survey data

2.7.7 *H. Results of the sensitivity analysis for the second step of the LASSO double selection procedure*

In the second step of the double selection procedure we then ran 50 probit models, one for each combination of *nfolds* and *seeds* with the respective control variables selected in the first step. To specify our model, we try different combinations of five random number seeds and ten different folds in the cross-validation [10,20,30,40,50,60,70,80,90,100] for each of the three models LM1, LM2 and LM3, to make sure that results do not differ depending on in how many parts the data is split for the train and test purposes.

Figure 2.16 shows the marginal effects for the ten different versions of folds as mean over all seeds. It can be seen that the marginal effects do not differ remarkably among the different models meaning that the number of folds has no effect on the results. Although different variables have been selected in the different models (see Table 2.4), marginal effects remain robust (see Figure 2.16) meaning that the choice and combination of control variables selected does not influence the magnitude and significance of our variables of interest *KnowAdopters* and *ObserveFields*.

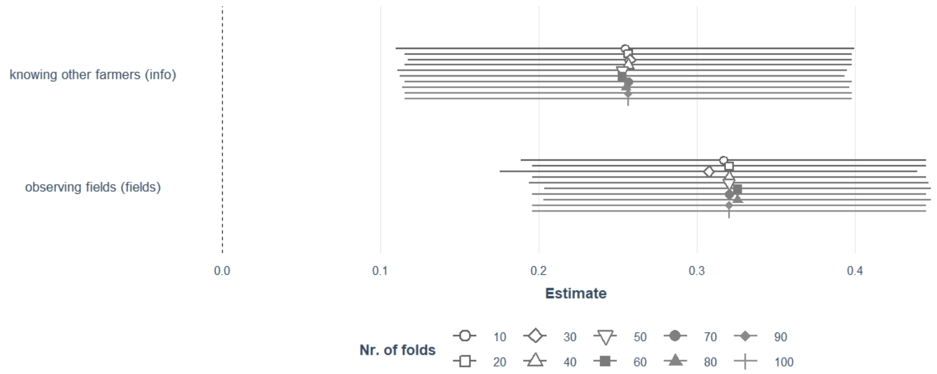


Figure 2.16: Marginal effects for different number of folds in the second step of the LASSO double selection procedure

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors.

We averaged the estimates for *KnowAdopters* and *ObserveFields* over all 50 specifications leading to an average marginal effect of 0.2550 for *KnowAdopters* and 0.3213 for *ObserveFields*.

In a third step we then compared the double selection model to other model variations (see Table 2.5). We exchanged the variable of *FactoryLocation_agg* with the one of *Association_agg*. While *FactoryLocation_agg* refers to the concrete location of the sugar factories in Germany, *Association_agg* reflects which county belongs to which sugar beet associations (see Figure 2.8). We could not detect any difference in the model outcomes. Additionally, we compared both specifications to "Full models", where all control variables are included without LASSO double selection.

Table 2.5: Comparison of different model specifications

Model	specification
FullModel_Association	Probit model with all variables from *ControlLasso* including *Association_agg* as explanatory variables
FullModel_FactoryLocation	Probit model with all variables from *ControlLasso* including *FactoryLocation_agg* as explanatory variables

DoublseSelection_Association	Nfolds= 50, double selection including *Association_agg* as explanatory variable in *ControlExogenous*
DoubleSelection_FactoryLocation	Nfolds= 50, double selection including *FactoryLocation_agg* as explanatory variable in *ControlExogenous*
Pre-registration (PR1)	Original model as specified in the pre-registration

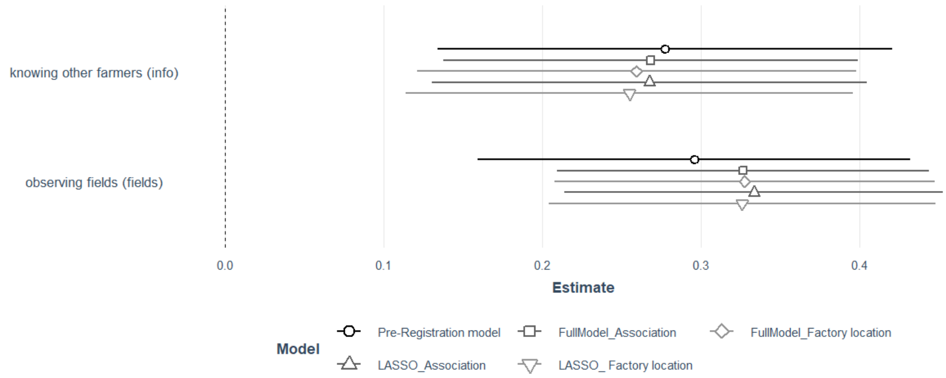


Figure 2.17: Comparison of marginal effects for different model specifications as described in Table 2.5

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors.

It can be seen that the marginal effects for *KnowAdopters* and *ObserveFields* remain positive and within the same magnitude for all models. Knowing at least one other adopter increases the likelihood of adoption by around 25-27 % and observing at least one field by around 31-33 % ceteris paribus, all effects are statistically significant at the 1 % level. These results support the findings from the different LASSO models, that the mean marginal effect for *KnowAdopters* lies at around 26 % and for *ObserveFields* at around 32 %.

2.7.8 *I. Intention to use mechanical weeding technologies in the future*

As an extension of the above shown model we run an ordered probit model with the same explanatory variables as above but with *Intention to adopt* as dependent variable in Model PR2:

$$\Pr(IntentionAdopt_{ti}=\mathrm{j}|KnowAdopters_{ti},\ ObserveFields_{ti}, Control_{ti}, \beta, \boldsymbol{\gamma})$$

$$= \Phi(\beta_0 + \beta_1 KnowAdopters_{ti} + \beta_2 ObserveFields_{ti} + \boldsymbol{\gamma} Control_{ti} + \varepsilon_{ti}) \quad \text{(A2)}$$

wherein Φ denotes the normal cumulative distribution function, the β's denote scalars and γ a vector of coefficients to be estimated. The intention to adopt *IntentionAdopt* can take five different levels *j* with *j* = 0 if no intention, 1 if low intention, 2 if middle intention, 3 if high intention, and 4 if technique is already adopted[††††]. We ran three models on intention, one for each type of technology *t* being t =1 for traditional mechanical weeding i.e. tractor-mounted machinery, t = 2 for modern mechanical weeding i.e. tractor-mounted but camera- or GPS-steered machinery and t = 3 for autonomous weeding devices.

Results

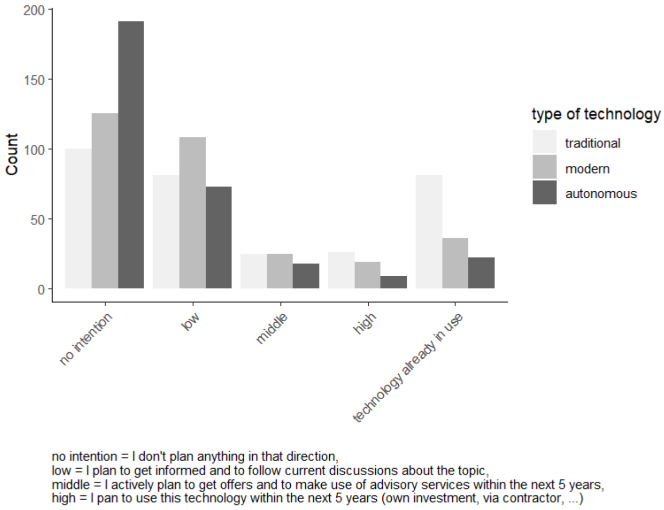


Figure 2.18: Intention to use different types of mechanical weeding in the future

Source: own presentation based on survey data

[††††]Original survey text: „0 = I am not planning anything; 1 = I think about getting more information and follow current discussions and literature; 2 = I am actively seeking for offers and I want to take part in a consultation within the next 5 years; 3 = I plan to use this technique within the next 5 years (own investment, contractors, ...); 4 = I am already using this technique"

Figure 2.19 shows the marginal effects for *KnowAdopters* and *ObserveFields* for the three ordered logit models on intention for the three types of mechanical weeding: traditional, modern and autonomous.

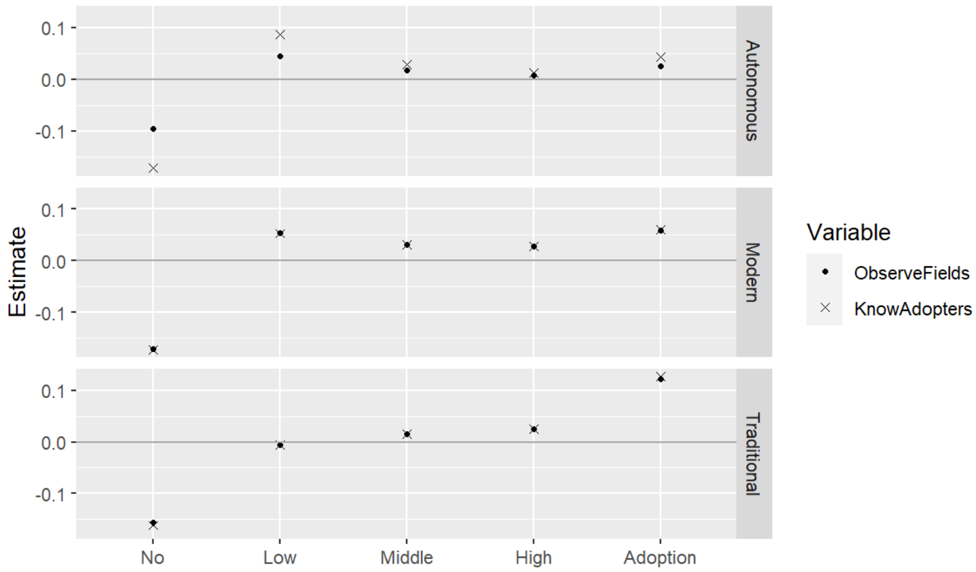


Figure 2.19: Marginal effects for *KnowAdopters* and *ObserveFields* on the Intention to use different types of mechanical weeding techniques in the future

Note: Dependent variable = Intention levels (no, low, middle, high, adoption), Observations: 294.

The likelihood of having "no intention" to use mechanical weeding in the future decreases for all three types of technology if at least one adopter is known and if at least one field is observed, ceteris paribus. The marginal effects turn positive for the other levels of intention in most cases meaning that knowing at least one adopter or observing at least one field increases the likelihood of having some (low, middle, high, adoption) intention to use a certain mechanical weeding technology in the future. This goes along with findings from Bessette et al. (2019) who found that seeking for information on ecological weed management is driven by other farmers behavior through social norms, hence seeing mechanically weeded fields or talking to farmers might trigger the search for information which we define as (low or middle) intention. Though the results have to be interpreted with care as statistical significance is only present in some cases and the economic effect is small.

The marginal effects are quite similar for *KnowAdopters* and O*bserveFields*, especially for traditional and modern technologies. For autonomous weeding devices *KnowAdopters* has a larger effect on the likelihood to have a low level of intention than O*bserveFields* which might be due to the rare possibilities to actually observe a weeding robot and its effects in use.

2.7.9 *J. Results alongside research question 2*

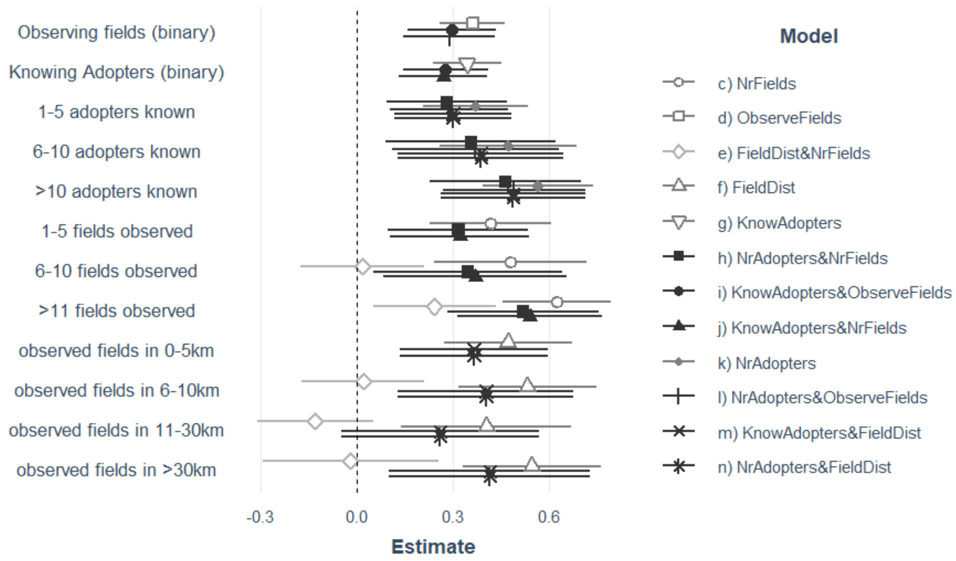


Figure 2.20: Marginal effects of models examined for prediction accuracy depending on variables included

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors, models including only one variable are depicted in grey (c,d,f,g,k), those including two variables are black (h,i,j,l,m,n) and the model including the two field variables (e) is shown in light grey

2.7.10 *K. Selection of fields*

We found that the distance to other farmers' fields differs significantly between those who selected the fields vie the map compared to those who selected via single choice (based on a Fisher's exact test). Those who selected via map choose fields in closer distance, which might indicate that finding fields on the map, especially further away was difficult and time consuming. We found the same for the number of fields selected: those who selected via the map selected significantly less fields than those who selected via multiple choice (Fisher's exact test). This delivers insights into the value of our novel map tool. Results must be interpreted with regard to this potential bias meaning that the "true" radius of own fields and fields observed might be slightly larger.

2.7.11 *L. Results alongside research question 3*

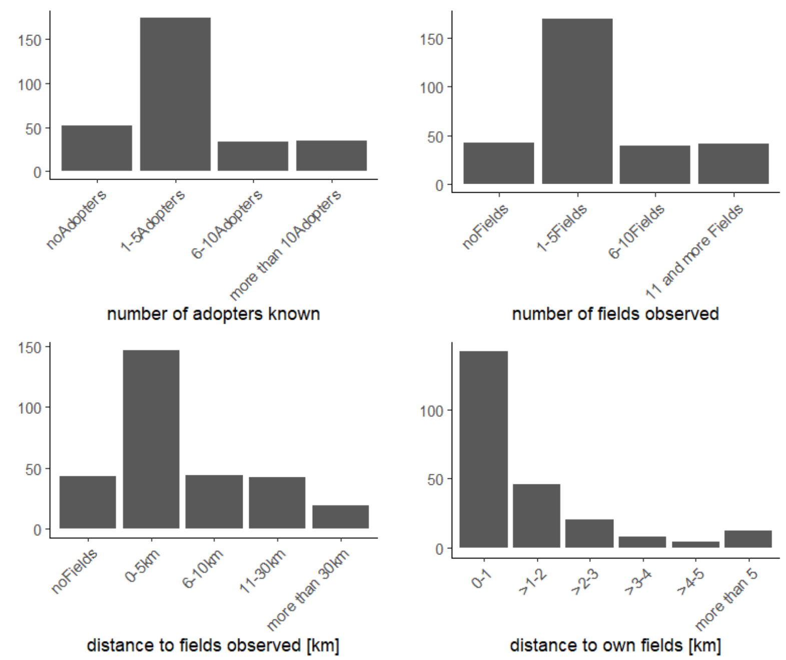


Figure 2.21: Size and structure of the network - descriptively

Note: For OwnFieldDist n= 232, subsample of those who selected own fields via map

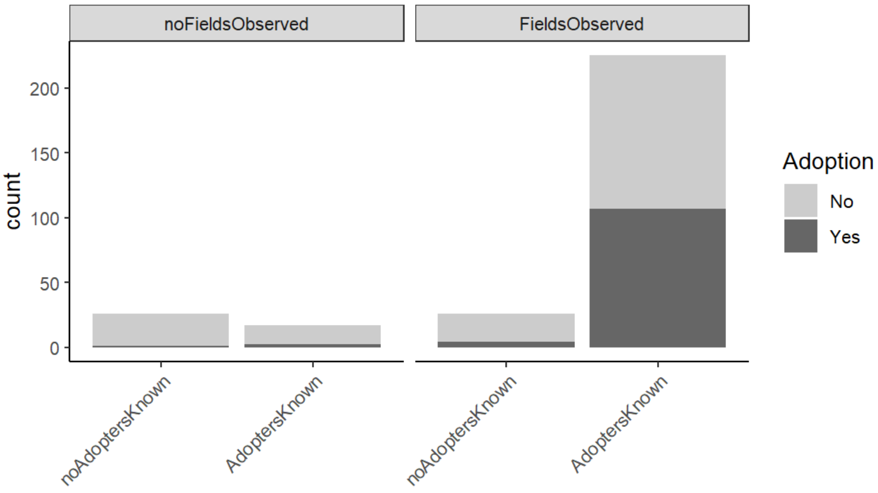


Figure 2.22: Share of adoption by field observation and knowing adopters

Source: own presentation based on own data

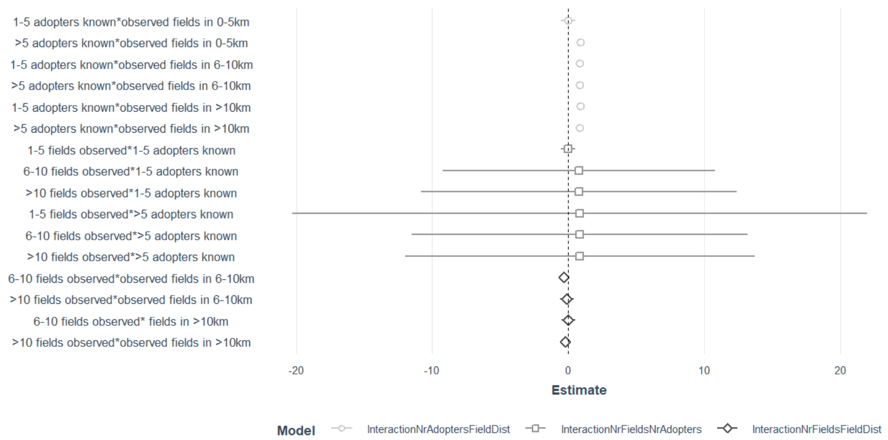


Figure 2.23: Marginal effects of the Interaction- Models

Note: Dependent variable = Adoption, Observations: 294, Displaying confidence interval of 0.95, partial effects for the average observation with robust and standardized standard errors.

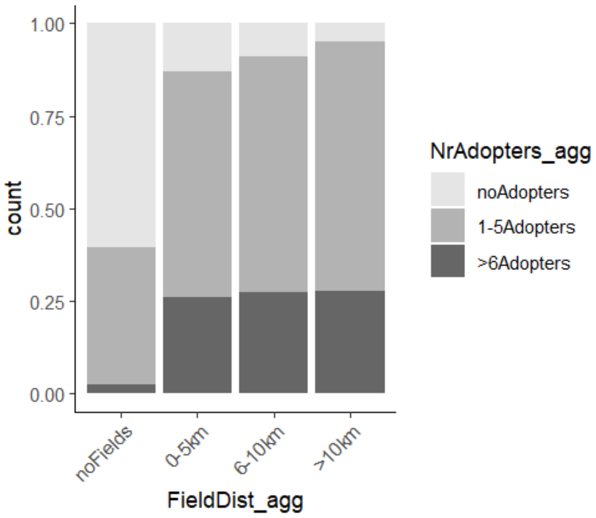


Figure 2.24: Correlation between *NrAdopters* and *FieldDist*

Source: own presentation based on survey data

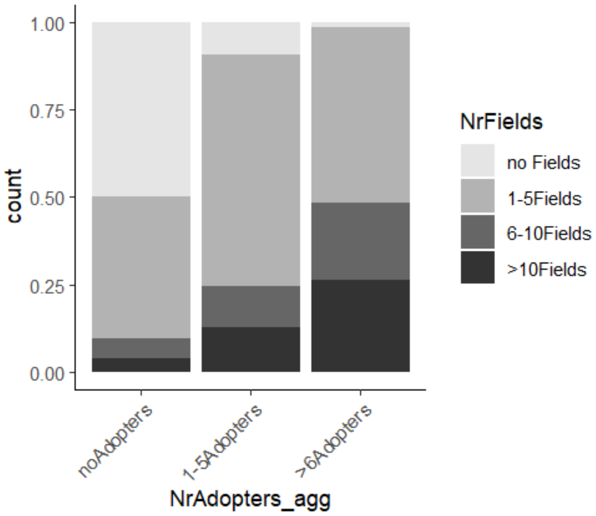


Figure 2.25: Correlation between *NrAdopters* and *NrFields*

Source: own presentation based on survey data

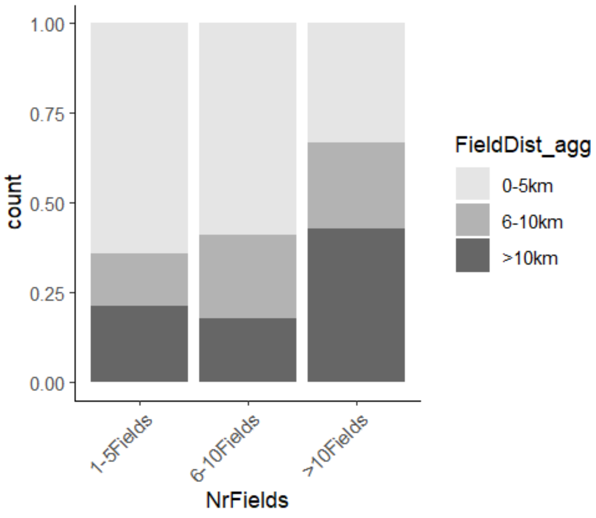


Figure 2.26: Correlation between *NrFields* and *FieldDist*

Source: own presentation based on survey data

2.7.12 *M. Demonstration farm findings*

To assess the effect of the minimal distance to demonstration farms (*MinDist_demo)*, we explored how this variable relates to the predicted probability of adoption in the pre-registration model PR1 (lower part of Figure 2.27). Most farms have a demonstration farm in less than 20 km radius (see histogram in upper part of Figure 2.27). The relation between minimal distance to demonstration farms and the predicted likelihood of adoption is convex and approaching zero, indicating that likelihood of adoption decreases with increasing minimal distance to demonstration farms. The effect of demonstration farms on adoption is rather local as it largest for farms close by (<10 km) and decreases at a high rate until the distance approaches 20 km. This result again supports our findings on the relevance of local information and is in line with previous studies on that topic (Arbuckle, 2017; Llewellyn, 2007; Mekonnen et al., 2022) and goes along with findings from Läpple et al. (2016) who identified spatial knowledge spillovers from research, education and advisory services influencing innovation in the agricultural sector. We assume that having a demonstration farm in the close neighborhood offers the possibility to 1) talk to adopters of mechanical weeding and 2) observe their fields and technologies in use. Hence again, both mechanisms behind peer effects seem to work here. Especially the effect of social learning among peers through demonstration farms has been proven in a French case study (Deperrois, Fadhuile, & Subervie, n.d. forthcoming; Lapierre, Sauquet, & Subervie, 2019). Besides a reduction of the perceived complexity through social learning, social norms could come into play at an additional level: demonstration farms might be more often visited by other farmers as well as by consumers and farmers might feel more social pressure to farm environmentally friendly or to show their engagement for the environment (Kuhfuss et al., 2016; Mzoughi, 2011; e.g. Willock et al., 2008).

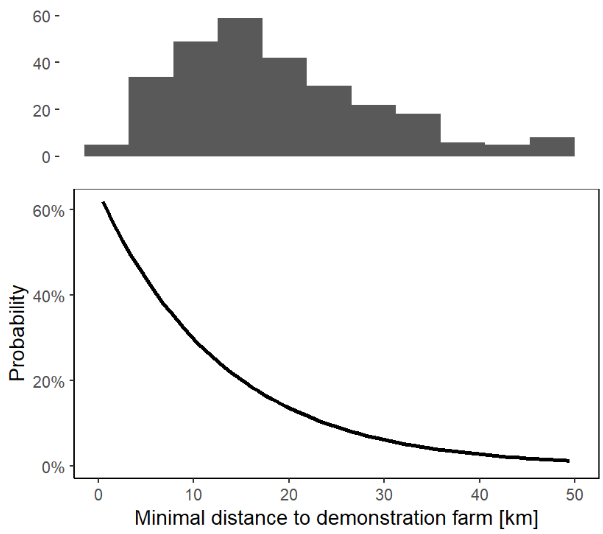


Figure 2.27: The probability that an 'average' farm adopts mechanical weeding for varying distance to demonstration farms

Note: All other variables are held constant at their means.

Chapter 3
Are Farmers Algorithm-Averse? The Case of Decision Support Tools in Crop Management*

Abstract. The advancement of artificial intelligence (AI) technologies has the potential to improve farming efficiency globally, with decision support tools (DSTs) representing a particularly promising application. However, evidence from medical and financial domains reveals a user reluctance to accept AI-based recommendations, even when they outperform human alternatives. This is a phenomenon known as "algorithm aversion" (AA). This study is the first to examine this phenomenon in an agricultural setting. Drawing on survey data from a representative sample of 250 German farmers, we assessed farmers' intention to use and their willingness-to-pay for DSTs for wheat fungicide application either based on AI or a human advisor. We implemented a novel Bayesian probabilistic programming workflow tailored to experimental studies, enabling a joint analysis that integrates an extended version of the unified theory of acceptance and use of technology with an economic experiment. Our results indicate that AA plays an important role in farmers' decision-making. For most farmers, an AI-based DST must outperform a human advisor by 11–30% to be considered equally valuable. Similarly, an AI-based DST with equivalent performance must be 21–56% less expensive than the human advisor to be preferred. These findings signify the importance of examining AA as a cognitive bias that may hinder the adoption of promising AI technologies in agriculture.

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

* This chapter is to date under review at the *American Journal of Agricultural Economics* as MASSFELLER, A., HERMANN, D., LEYENS, A., STORM, H. (2025). "Are Farmers Algorithm-Averse? The Case of Decision Support Tools in Crop Management". Only minor edits have been made for the purpose of this dissertation.

3.1 **Introduction**

Artificial intelligence (AI)[†] is a central component of the ongoing 4th Agricultural Revolution, which is marked by the increasing integration of information and communication technology into farming systems (Khanna et al., 2024; Walter et al., 2017). Unlike earlier information systems, AI technologies can learn from vast amounts of complex, high-resolution data using machine-learning algorithms, thereby improving predictive accuracy over time (Jarrahi et al., 2022). This adaptive learning capability allows AI tools to generate more accurate recommendations and reduce uncertainty in crop management (Khanna et al., 2024).

A key application of AI in agriculture is the use of decision support tools (DSTs), which assist farmers in making optimal decisions under conditions of complexity and uncertainty (Rose et al., 2016; Shtienberg, 2013). In recent years, public advisory bodies and private firms have introduced AI-based DSTs designed to enhance productivity, optimize resource use, and support climate adaptation strategies in farming (Yousaf et al., 2023). These tools offer advanced capabilities for data acquisition and predictive analytics by incorporating real-time information, allowing for more precise recommendations than traditional, non-AI-based DSTs (Gautron et al., 2022; Khanna et al., 2024; Lázaro et al., 2021; Storm et al., 2024). However, realizing the full potential of AI-DSTs depends on farmers' willingness to adopt them. Despite the promise of improved input efficiency (Lázaro et al., 2021; Helps et al., 2024; Giulivi et al., 2023; Lazaro et al., 2023), prior studies have indicated that farmers tend to rely more on peer networks and advisory services than on digital tools (Skaalsveen et al., 2020; Kiraly et al., 2023).

This reluctance towards (potentially superior) recommendations from algorithmic decision support is known as "algorithm aversion" (AA), a

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[†] We refer to Artificial Intelligence (AI) as one type of an algorithm and follow the definition by the EU of AI as " a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" (European Commission 2024b).

cognitive bias in which individuals favor human advice over algorithmic input, even when the latter performs demonstrably better[‡] (Dietvorst et al., 2015). Although AA has been widely studied in fields of medicine (Longoni et al., 2019) and finance (Cohen et al., 2021), it has not yet been explored in the context of agricultural decision-making (e.g., Mahmud et al., 2022). From an economic standpoint, AA represents a deviation from rational behavior in which individuals forgo algorithmic recommendations in favor of potentially worse human advice. Given the ongoing development of AI-DSTs in agriculture (Gautron et al., 2022; Yousaf et al., 2023) and their potential for improving efficient resource usage to decrease environmental degradation while allowing for high yields, there is a crucial need for understanding such behavioral deviations to foster effective technology adoption.

Accordingly, this study seeks to answer the following research question: "What role does AA play in farmers' intention to use AI-based DSTs?" To answer this, we conducted a pre-registered, ethically approved online survey of 250 German arable farmers in the autumn of 2024. The survey elicited their intention to use AI-DSTs and their willingness-to-pay (WTP) for AI- versus human-based advisory services. For survey design and statistical analysis, we employed a Bayesian probabilistic programming (PP) workflow (Storm et al., 2024; Gelman et al., 2020; McElreath, 2018), which we propose as an adaptable framework for experimental studies.

Our findings suggest that AA plays an important role in both farmers' intention to use and their WTP for AI-DSTs. Most farmers in our sample preferred human advisors, even when those advisors performed worse than AI-DSTs. We calculated the performance premium (i.e., the additional level of performance required for an AI-DST to be valued equally to a human advisor) and found that for 90% of the posterior samples, AI-DST needed to perform 11–30% better. Similarly, we derived a price premium, showing that, to be preferred, an equally performing AI-DST would need to cost 21–

[‡] Throughout this study, we follow Dietvorst et al. (2015) and define the algorithm as "any evidence-based forecasting formula or rule." Thus, the term includes statistical models, decision rules, and all other mechanical procedures that can be used for forecasting."

56% less than its human counterpart. These results also indicate that some share of the posterior samples would prefer a human advisor over an AI-DST even if the performance of the human advisor is 30% lower and if it is more than 56% more expensive, respectively.

This study contributes to the literature empirically and methodologically. Empirically, we are the first to both examine and quantify the role of AA in farmers' decision-making through an experimental study. Although AA and its counterpart, algorithm appreciation, have been explored in health, finance, psychology, information technology, and business (Mahmud et al., 2022), it has not been studied within the context of agriculture. Moreover, field experiments and surveys addressing this phenomenon are rare (Mahmud et al., 2022).

To date, AA as a phenomenon explaining deviations from rational behavior has not been considered in the literature on farmers' decision-making, especially regarding digital technology adoption and DST use. Although numerous studies have explored factors related to farmers' DST usage decisions (Shtienberg, 2013; Rojo-Gimeno et al., 2019; Kerebel et al., 2013; Bessette et al., 2019; Rose et al., 2016; Rose et al., 2018), gaps remain in fully understanding farmer behavior. While behavioral factors underlying deviations from rational decision-making have been identified and classified (Déssart et al., 2019), few studies have examined cognitive biases specific to AI use. Whereas broader human–AI interactions have been reviewed (e.g., Kaplan et al., 2023), little attention has been given to how farmers, as a unique subgroup, relate to AI technologies (e.g., Orn et al., 2020; De la Peña and Granados, 2024). As a theoretical extension, we integrate AA into the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003). Although UTAUT has been applied to farmers' technology adoption (Otter and Deutsch 2023; von Veltheim et al., 2022; Giua et al., 2022; Michels et al., 2020), its adaptation to include AI-specific factors has thus far been limited to the context of business managers (Cao et al., 2021). In our study, AA is operationalized as the effect of AI-anxiety (AIA) on behavioral intention (BI).

Methodologically, we demonstrate how a Bayesian PP workflow (Storm et al., 2024; Gelman et al., 2020; McElreath, 2018) can be adapted for use in experimental and survey-based research in agricultural economics. This approach enhances transparency by grounding the analysis in a clearly defined, theoretically motivated data-generating process (DGP), which enables the pretesting of survey instruments and experimental design using synthetic data before real data collection begins. It also supports validation of code implementation, model inference, and result visualization, all of which are documented in the pre-registration. This enhances the theoretical basis for the analysis, minimizes implementation errors, and increases transparency.

In terms of benefits in the statistical analysis, the Bayesian approach allows for a unified analysis of UTAUT survey and WTP experiment data by treating AIA as a common latent driver of AA. Additionally, Bayesian methods offer distinct advantages in expressing and interpreting (parameter) uncertainty, compared with frequentist approaches (Storm et al., 2024). To our knowledge, this is one of the first applications of the full Bayesian workflow across all stages of an experimental study in this domain (see e.g., Stranieri et al., 2022; Leyens et al., 2024; for an application adopting Bayesian approaches in parts of the experimental settings and Varacca, 2024 for the proposal of a Bayesian estimation in causal mediation analysis).

The remainder of the paper is structured accordingly. In Section 2, we present the Bayesian PP workflow for experimental studies, which includes defining the quantity of interest, deriving the statistical (causal) model, and constructing the DGP, which combines the statistical model and the experimental design. We also test our assumptions using synthetic data before applying the model to real survey data. Section 3 presents the empirical results, followed by discussion and conclusions in Section 4.

3.2 **Bayesian PP Workflow for Experimental Studies**

We adapted and extended the PP workflow developed by Storm et al. (2024) to the context of an experimental study, as illustrated in Fig. 3.1.

Although the general structure of the workflow remains consistent, its primary innovation lies in the development of the DGP (Step 3), which requires three iterative sub-steps: variable operationalization, statistical model formulation, and experimental framework design. These steps are repeatedly refined to ensure internal consistency and empirical robustness. Together, Steps 1–3 formalize our variable of interest, AA.

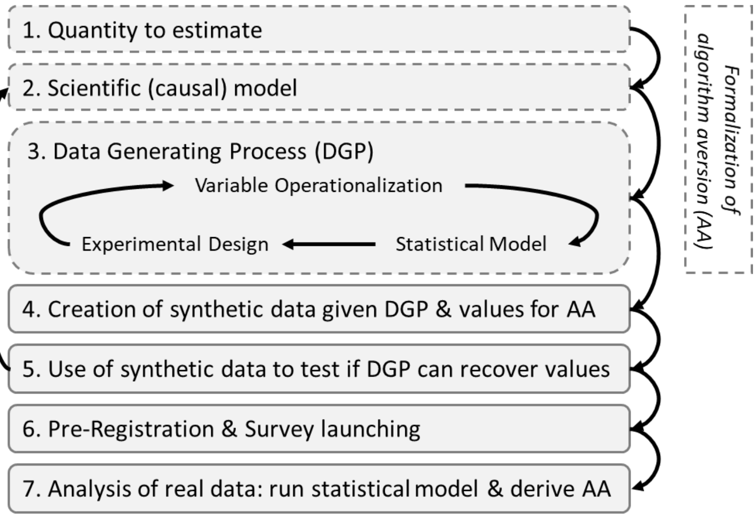


Figure 3.1: Bayesian probabilistic programming workflow for experimental studies

3.2.1 *Quantity to Estimate and Topical Background*

We conceptualize AA as the effect of AI-anxiety (AIA) on decision outcomes based on willingness-to-pay (WTP) and behavioral intention (BI). AIA refers to the discomfort or fear individuals may experience due to perceived loss of control over AI technologies, often stemming from misunderstandings about technological capabilities, uncertainty around machine autonomy, and limited awareness of the broader sociotechnical context (Johnson & Verdicchio, 2017). Given the increasing integration of AI into everyday (and agricultural) life, we argue that AIA should be incorporated as a behavioral factor in studies of farmers' decision-making.

We focus specifically on farmers' input-use decisions in crop production, which link economic behaviors to agronomic outcomes involving resources such as seeds, water, fertilizers, and pesticides. These decisions are inherently complex and involve evaluating trade-offs, such as the potential yield loss due to pests versus the costs of treatment under uncertainty and risk from factors like weather, disease pressure, market fluctuations, and for human health (Rosburg & Menapace, 2018; Chatzimichael, 2022; Maertens et al., 2021). Historically, farmers have relied on extension services, personal experience, and peer networks to guide such decisions (Läpple & Barham, 2019; Krishnan & Patnam, 2014). However, digitalization has increased the relevance of DSTs as a source of decision-making support in agriculture (Walter et al., 2017; Finger et al., 2019).

Compared with human advisors, (AI-based) DSTs offer two major advantages. First, they are highly scalable and more cost-efficient (Spielman et al., 2021; Van Campenhout et al., 2021). Second, they can integrate vast, unstructured real-time data from in-field sensors or drones with machine-learning algorithms, enabling enhanced precision and adaptive learning based on historical outcomes (Gautron et al., 2022; Khanna et al., 2024; Storm et al., 2024).

Despite these benefits, many farmers exhibit resistance even to non-AI-DSTs and often deviate from optimal input-use recommendations (Möhring et al., 2020; Skevas et al., 2014; Gars et al., 2025; Oyinbo et al., 2022). This behavior cannot be explained by economic factors alone; instead, a range of behavioral factors (e.g., personal beliefs, risk preferences or peer pressure) play important roles (Oyinbo et al., 2022; Giulivi et al., 2023; Gars et al., 2025; Van Campenhout et al., 2021; Spielman et al., 2021). However, behavioral factors specific to AI-DST adoption in agriculture remain underexplored. To address this gap, we introduce AIA as an additional dispositional factor within the framework proposed by Déssart et al. (2019), which classifies cognitive, social, and dispositional factors on sustainable farming practice adoption. As defined by Malle (2011), a dispositional factor reflects an individual’s general tendency to act in a certain way. In this study, we assess the influence of AIA on farmers’ (hypothetical) use decisions for AI-DSTs, both in terms of stated intention and WTP, capturing this relationship as AA.

Our specific application involves AI-DSTs that provide recommendations for fungicide application in wheat production. Efficient fungicide use is essential to balancing agricultural productivity with environmental protection. On the one hand, fungicides help preventing yield losses and maintain crop quality, thereby contributing to global food security and safety (Figueroa et al., 2018; Oerke, 2006; Schneider et al., 2023). On the other hand, their use can pose risks to human health and ecosystems, including biodiversity loss (Fritsch et al., 2024; Geiger et al., 2010; McMahon et al., 2012; Hossain et al., 2017). Enhancing the efficiency and effectiveness of fungicide applications is therefore a critical global challenge and is explicitly addressed in international (CBD, 2025), regional (European Commission, 2020), and national (USDA, 2025; USDA NIFA, 2025) policy frameworks. In both the EU and the US, farmers are encouraged to adhere to integrated pest management guidelines, which recommend pesticide applications only when infestation thresholds are met (European Commission, 2024a; Smith & Van den Bosch, 1967; 7 US Code § 136r-1, 2018; USDA, 2025).

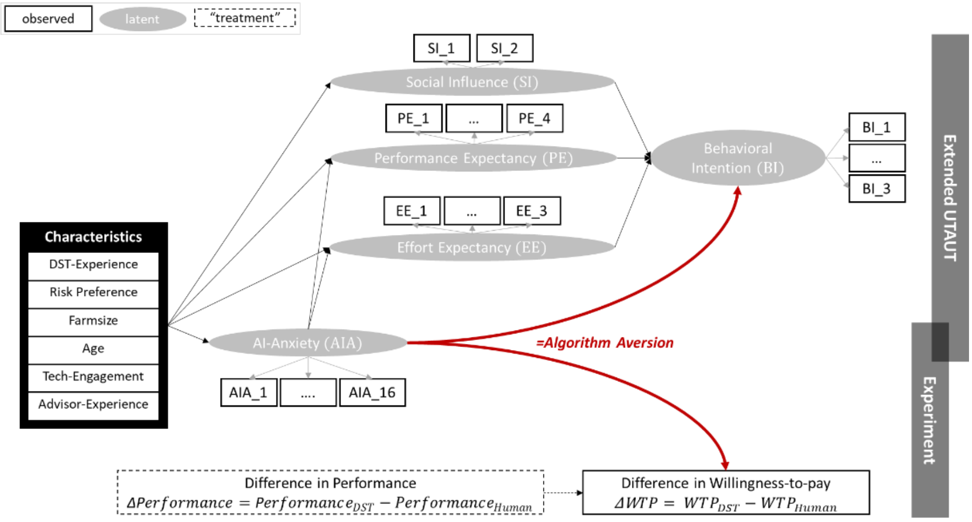
3.2.2 *Scientific (Causal) Model*

Having defined our quantity to estimate based on the topical background, AA, we proceed to the second step of the PP workflow: specifying the scientific (causal) model. This model is visually represented using a directed acyclic graph (DAG), shown in Fig. 3.2. DAGs are a powerful tool for causal inference, increasingly used in both general economics (Imbens, 2020; Pearl & Mackenzie, 2018; Huntington-Klein, 2021) and agricultural economics (Henningsen et al., 2024). They allow researchers to formalize assumptions about both observed and latent relationships among variables (Angrist & Pischke, 2009; McElreath, 2018).

At the center of our DAG is the latent construct, AIA, which is posited to influence both BI (upper portion of the graph) and WTP for different types of decision support (DS; lower portion). This dual influence constitutes AA (indicated by red arrows). Following Kaplan et al. (2023), who identified ability- and trait-based predictors of AI trust, and Mahmud et al. (2022), who emphasized the role of personal factors in AA, we hypothesize that AIA, like social influence (SI), performance expectancy (PE), and effort expectancy (EE), is shaped by farmers' personal and farm-level characteristics. Building on Venkatesh (2000; 2003), we further assume that AIA influences both PE and EE. These belief constructs, in turn, affect the farmer's BI to use AI-DSTs.[§]

Figure 3.2: Directed acyclic graph of the scientific model

In the experimental component (lower part of the DAG), we infer preferences for advisory options based on the difference in WTP for human



advice versus AI-based DST recommendations. This difference is denoted as ΔWTP and is modeled as a function of the difference in past performance between two advisors, $\Delta Performance$ and AIA. The influence of AIA on ΔWTP represents AA. Conceptually, AIA introduces a bias or "penalty" that distorts the translation of $\Delta Performance$ into ΔWTP.

Notably, the Bayesian PP framework enables simultaneous estimation of both the latent AIA variable and its effects on BI and ΔWTP, as depicted in

[§] Note that we deviate from the traditional UTAUT set up by considering the personal characteristics (age, experience) as antecedents of AI-Anxiety rather than mediators. Furthermore, we do not include facilitating conditions as they only relate to the actual use behavior that we do not measure. We do not ask for Voluntariness of use as it is given for all participants and we do not include gender as AI-Anxiety has not been found to vary by gender (Mahmud et al. 2022) and other studies using the UTAUT for German farmers' technology adoption decisions either do not find a significant effect of gender (Rübcke von Veltheim, Theuvsen and Heise 2022).

the DAG (red arrows). This unified approach enhances consistency between the attitudinal and experimental components of the study.

3.2.3 *Data-Generating Process*

Variable Operationalization

To measure the dispositional factor of AIA, we use the validated AIA scale developed by Wang and Wang (2022), which incorporates 16 statements that capture each individual's level of AIA. These are reflected in the AIA_1–AIA_{16} boxes in Fig. 3.2 and are measured on a 7-point Likert scale (1 = "Totally disagree," 4 = "Indifferent," 7 = "Totally agree"). For the full list of statements, see the complete survey in Appendix A.

The selection of personal characteristics and latent constructs (i.e., SI, PE, and EE) and the corresponding statements (white boxes in Fig. 3.2) are measured on the same 7-point Likert scale and formulated based on the original UTAUT items from Venkatesh et al. (2003), prior studies applying UTAUT to similar technology adoption decisions among German farmers (Otter & Deutsch, 2023; Von Veltheim et al., 2022; Giua et al., 2022; Michels et al., 2020), and a study on DST adoption in pesticide management (Akaka et al., 2024). For more detail on the selected variables and related hypotheses, see our pre-registration.[**]

In the experimental component, we measured ΔWTP as the difference between each farmer's WTP (euro) for AI-DST versus human DS. Thus, ΔWTP is positive if the AI-DST is preferred, negative if the human advisor is preferred, and zero if both are valued equally.

The $\Delta Performance$ variable is explicitly manipulated by providing participants with information about the historical performance of each advisory option. Performance is expressed as the percentage of correct past recommendations, where a "correct recommendation" is one that improves economic outcomes relative to a status quo with no advisory input. We then calculate $\Delta Performance$ as the difference between the performance probability of the AI-DST and that of the human DS. As a result,

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

$\Delta Performance > 0$ when the AI-DST outperforms the human advisor, $\Delta Performance < 0$ when the human performs better, and $\Delta Performance = 0$ when both perform equally well.

Statistical Model

Having operationalized our variables, we next formulate the statistical model underlying the DGP, following the DAG depicted in Fig. 3.2.

Formation of Latent Constructs

We begin by defining a vector of personal and farm-level characteristics $\boldsymbol{x}$ for each individual *i*:

$$\boldsymbol{x_i} = [Age_i, DSTExperience_i, RiskPreferences_i, AdvisorExperience_i, Farmsize_i, TechEngagement_i] \tag{1}$$

For each latent construct, C, we define the mean, $\mu_{i,\mathrm{C}}$, for $\forall\, \boldsymbol{C} = \{\, AIA, PE, EE, SI\}$ in accordance with the relationships specified in the DAG (Fig. 3.2). We assume simple linear relationships between constructs and personal characteristics, $\boldsymbol{x_i}$, as follows:

$$\mu_{i,AIA} = \alpha_{i,AIA} + \boldsymbol{\beta'}_{i,AIA} * \boldsymbol{x_i} \tag{2}$$

$$\mu_{i,SI} = \boldsymbol{\beta'}_{i,SI} * \boldsymbol{x_i} \tag{3}$$

$$\mu_{i,C} = \boldsymbol{\beta'}_{i,C} * \boldsymbol{x_i} + \theta AIA_i \qquad \forall\, \boldsymbol{C} = \{\, PE, EE\}' \tag{4}$$

Formation of Likert-Scale Statements

Each individual, i, evaluates a set of n statements, $ST_{i,n}$ per latent construct using a 7-point Likert scale (see Fig. 3.2 and Appendix A). To accurately capture the latent constructs, we emphasize the need for Bayesian modeling of Likert-scale responses, following item response theory (Andrich, 2016; Andersen, 1997) and the rating scale model (Andrich, 2005; 2016), as implemented in prior works by Fox (2010), Stranieri (2022), and Varacca (2024).

A key modeling challenge with ordered categorical variables is that the differences between response values on a Likert scale are not necessarily equal. For example, moving from "Disagree" (2) to "Rather disagree" (3) may require less subjective change than moving from "Agree" (6) to "Strongly agree" (7) (Bürkner & Vuorre, 2019; Liddell & Kruschke, 2018). The goal is to map the underlying linear latent variable onto the categorical scale appropriately (McElreath, 2018).

Following McElreath (2018), we use a cumulative link function via an ordered logistic distribution. This requires estimating cut points k_{ST}, representing the thresholds at which respondents switch from one response value to the next. These cut points are part of the DGP and are estimated during the inference stage, enabling nuanced interpretation of each statement without assuming uniform thresholds across statements and constructs. This improves the flexibility and validity of the measurement model. We specify prior distributions for the cut points in the subsequent section of this paper.

$$Pr\left(ST_{i,n} = k_{ST_n}\right) = Pr\left(ST_{i,n} \leq k_{ST_n}\right) - Pr\ (ST_{i,n} \leq k_{ST_n} - 1) \qquad (5)$$

$$ST_{i,n} \sim OrderedLogit(\mu_{i,\mathrm{C}}, \boldsymbol{\kappa}_k) \qquad (6)$$

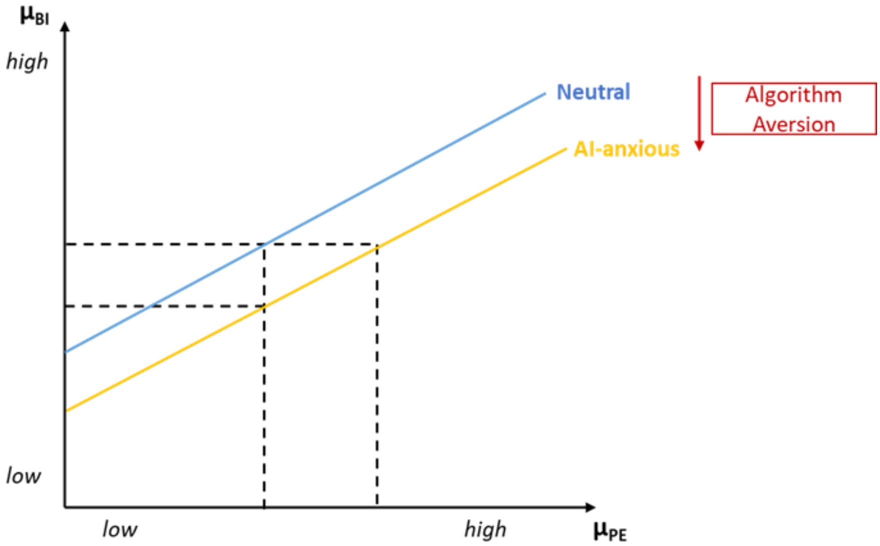
UTAUT

To estimate the $UTAUT$ outcome variable, we modeled the mean latent BI as μ_{BI_i}, a linear function of the latent constructs' mean, $\mu_{i,C}$, and associated coefficients $\boldsymbol{\gamma'}_i$, in accordance with the DAG. These behavioral intention statements are modeled using the same ordered logistic approach described above.

$$\mu_{i,BI} = \sum_{c \in C} \gamma'_{i,c} * \mu_{i,\mathrm{c}} \qquad (7)$$

As shown in Fig. 3.3 and captured by Eq. (7), AA manifests when, all else being equal, an AI-anxious individual (yellow line) exhibits a lower BI than an AI-neutral individual (blue line), given the same level of PE. In other words, the "translation" from PE into BI, both measured at an ordinal scale, would be distorted by AIA. Statistically spoken, AA materializes as a negative value for $\gamma_{i,AIA}$, representing a downward shift in the BI line for individuals with high AIA.

Figure 3.3: Statistical model of UTAUT with PE, EE and SI at their means.



Experiment

We next constructed the statistical model for the experiment based on the DAG (Fig. 3.2). The observed outcome, ΔWTP, is assumed to follow a normal distribution as a function of a linear combination of the performance difference, $\Delta Performance$, and $\mu_{i,AIA}$:

$$\Delta WTP_i \sim N(\beta_{i,\Delta Performance} * \Delta Performance + \beta_{i,AA} * \mu_{i,AIA}, \sigma_{WTP}) \quad (8)$$

$\Delta Performance$ is defined as the difference in performance between the AI-DST and the human advisor. This is expressed as the proportion of correct past recommendations, with values of 0.85, 0.90, and 0.95 used for both advice types. As a result, there are five possible values for $\Delta Performance$:

$$\Delta Performance = [\Delta_1, \Delta_2, \Delta_3, \Delta_4, \Delta_5] \quad (9)$$

$$\text{and } \Delta_i \sim DiscreteUniform(\{-0.1, -0.05, 0, 0.05, 0.1\}) \quad for\ i = 1,2,3,4,5. \quad (10)$$

Figure 3.4 illustrates the model described by Eq. (8), where ΔWTP (y-axis) is plotted against $\Delta Performance$ (x-axis). We assume that if the AI-DST and human advisor perform equally well (i.e., $\Delta Performance = 0$), an AI-neutral person (blue line) would be indifferent between the two, implying $\Delta WTP = 0$, ceteris paribus. When the human advisor performs better, ΔWTP becomes negative, reflecting a preference for the human. Conversely, a better-performing AI-DST yields a positive ΔWTP. This relationship is captured by a positive coefficient $\beta_{i,\Delta Performance}$.

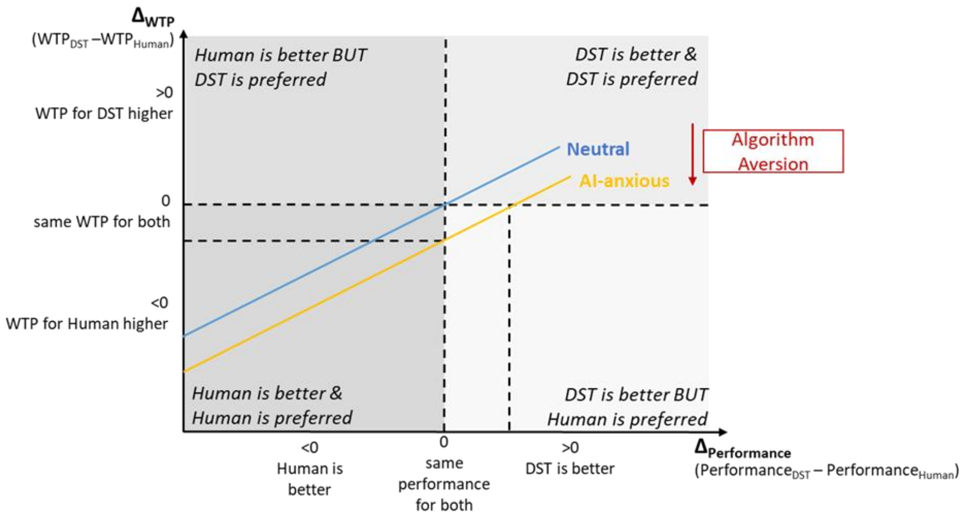


Figure 3.4: Graphical depiction of the statistical model for the experiment, ceteris paribus

In contrast, a person with higher AIA (yellow line) may prefer the human advisor even if both options perform equally or the AI performs better. This aversion is represented as a downward shift in the line, indicating a negative coefficient $\beta_{i,AA}$. In this context, AIA acts as a penalty that distorts the translation from $\Delta Performance$ to ΔWTP.

To capture relative ΔWTP, we normalize all WTP values by defining a base WTP for a human advisor with 90% performance. All other WTPs are expressed relative to this reference value.

In summary, our hypothesis is that AA plays an important role in farmers' decision-making. This is supported if $\gamma_{AIA} < 0$ or $\beta_{AA} < 0$. Either condition would imply that AIA negatively affects BI or ΔWTP. Graphically, this would be reflected as a downward shift of the lines for AI-anxious individuals compared with AI-neutral individuals, as shown in Figs. 3.3 and 3.4.

Choice of Priors

To complete the DGP, we defined priors for all model parameters. Following Varacca (2024), we used weakly informative priors, assuming zero-centered normal distributions as the variables are standardized. Prior predictive checks were conducted to determine parameter scales and ensure valid response distributions.

For the Likert-scale cut points, $\boldsymbol{\kappa}_k$, we used a standard deviation of 0.3 to ensure that all response categories are selected at least once. The final value for σ_{WTP} ensures that the range of ΔWTP (relative measure) is constrained between –1 and 1:

$$\alpha_{i,AIA} \sim N(0,1), \tag{11}$$

$$\boldsymbol{\beta'}_{\boldsymbol{i,C}} \sim N(0,0.5), \tag{12}$$

$$\boldsymbol{\gamma'}_{\boldsymbol{i,C}} \sim N(0,0.5), \tag{13}$$

$$\boldsymbol{\kappa}_k \sim N(0, 0.3), \tag{14}$$

$$\beta_{i,AA} \sim N(0,0.5), \tag{15}$$

$$\beta_{i,\Delta P} \sim N(0,0.5), \tag{16}$$

$$\sigma_{WTP} = 0.2. \tag{17}$$

Experimental Design and Sampling

With variable operationalization and the statistical model established, we next describe the experimental design. Note that the DGP development process is iterative; adjustments were made throughout (see Fig. 3.1). We adapted the experimental component from a study in the medical domain by Longoni et al. (2019), tailoring it to agricultural decision-making. Participants first read a brief introduction on fungicide use, which reminded them of the integrated weed management principle and outlined the two advisory options. Importantly, all variables other than the decision agent

(AI-DST or human advisor), including data inputs, delivery format, and timing, were held constant.

We defined "correct past recommendations" as the probability of achieving better economic outcomes than the status quo (i.e., without advisory input).[††] Each participant encountered three decision scenarios involving actual WTP choices (Fig. 3.5), each presenting different values for past performance, while keeping costs fixed.

From nine possible pairings (3 AI performance levels × 3 human performance levels), each respondent was randomly assigned three. Human performance values were drawn without replacement to ensure each level was shown once, and AI values were drawn with replacement. The slider for WTP began at 0 euro with an upper limit of 150 euro, reflecting market rates for public advisory services (Landwirtschaftskammer, 2024) and commercial DSTs (BASF, 2024).

The final survey launch and data collection were conducted online in cooperation with a market research company. In autumn 2024, we collected quantitative primary data from 250 German arable farmers. We selected Germany as the focal region because it is one of the largest wheat-exporting nations in Europe (FAO, 2024), where fungicides accounted for 24% of pesticide sales (by weight) in 2022 (Eurostat, 2024). As a result, German wheat yields are among the highest globally (Oerke, 2006; Gianessi & Williams, 2011).

[††] 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 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."

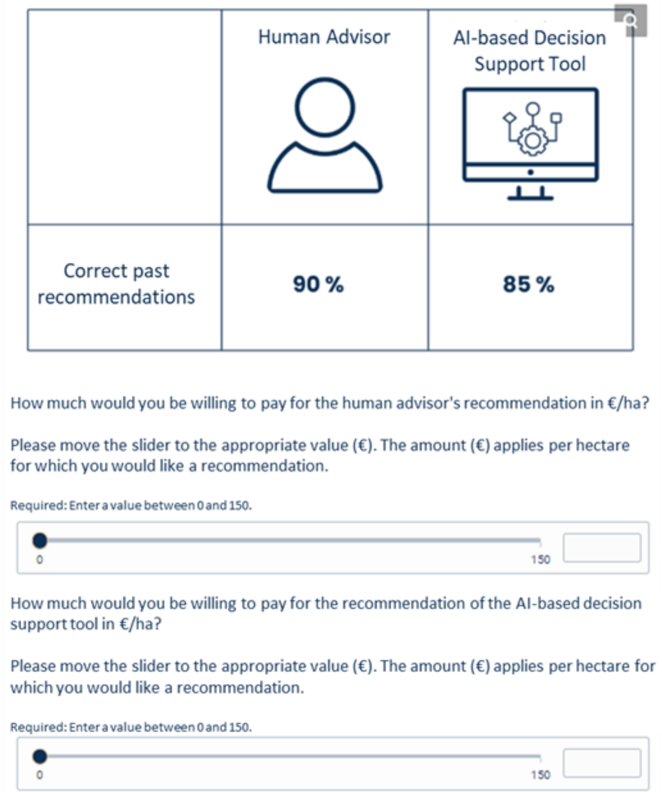


Figure 3.5: WTP choice design

Before the survey was launched, we obtained ethical clearance, pretested the questionnaire with experts and farmers, and pre-registered the study on the Open Science Framework.[‡‡] Participants were required to accept data protection terms, provide informed consent, and meet the eligibility criteria of being engaged in arable farming. Respondents were informed that participation was voluntary and that they could opt into a lottery at the end. Approximately 2% of participants were randomly selected to receive either a voucher or a non-cash prize.

To establish a common understanding of AI-DSTs, the questionnaire began with a short, neutral informational text defining DSTs and AI-based tools. The order of the two survey components (i.e., UTAUT-based statements and the experiment) was randomized across participants. At the end of the

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

questionnaire, we collected data on personal and farm characteristics. The full survey, including the experiment, instructions, and a schematic of the process, is provided in Appendix A.

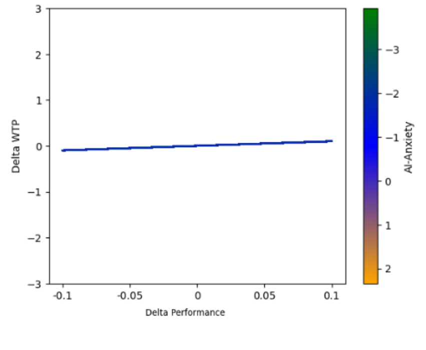
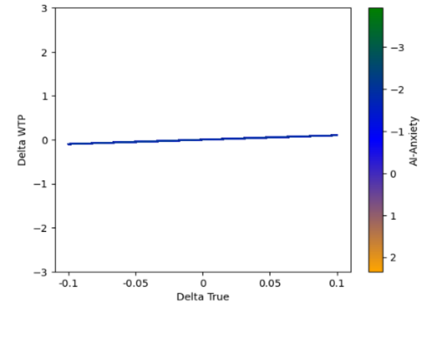
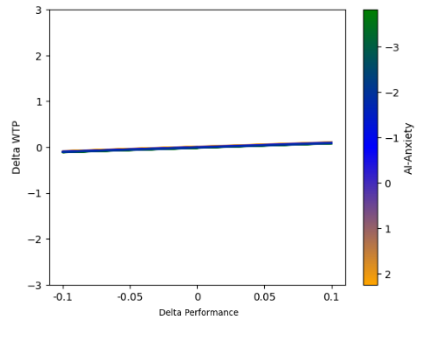
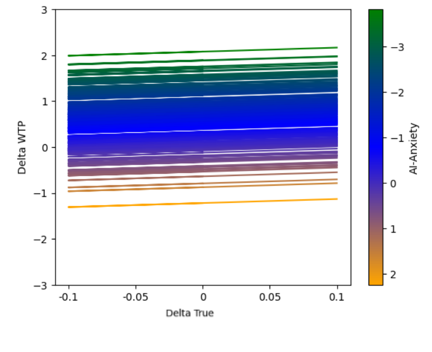
3.2.4 *Creation of Synthetic Data and Model Testing*

The conceptualization of AA and the DGP specification in Section 2.3 enabled us to conduct model testing, corresponding to Steps 4 and 5 in the PP workflow (Fig. 3.1). Specifically, we first generated synthetic data based on the DGP and then tested whether our Bayesian statistical model could recover the deliberately defined values of AA and our prior assumptions. This approach allows us to verify model functionality and simulate farmer responses to the survey, enabling pretesting of both the survey design and analytical pipeline.

Concretely, we created two synthetic datasets. In the first, AA was present (i.e., $\gamma_{AIA} < 0$ and $\beta_{AA} < 0$). In the second, AA was absent (i.e., $\gamma_{AIA} \geq 0$ and $\beta_{AA} \geq 0$). We then compared prior and posterior predictions of the coefficients of interest to evaluate whether the model could recover the parameters used to generate the synthetic data and how results would differ under competing hypotheses. In addition to testing inference capacity, this comparison supports the development of routines for illustrating the final results.

Table 3.1 presents the prior predictive distributions (top row) and posterior predictive distributions (bottom row). The left column corresponds to the dataset without AA, and the right column to the dataset with AA. To the left of each plot is a color scale representing latent AIA: negative values (green) indicate "negative AIA" or "algorithm appreciation," whereas positive values (yellow) indicate "positive AIA" or "high algorithm aversion".

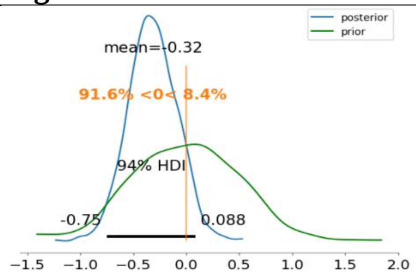
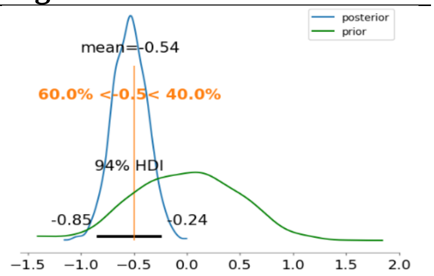
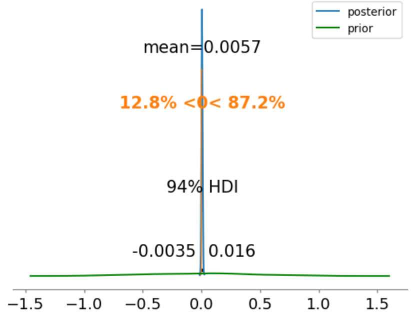
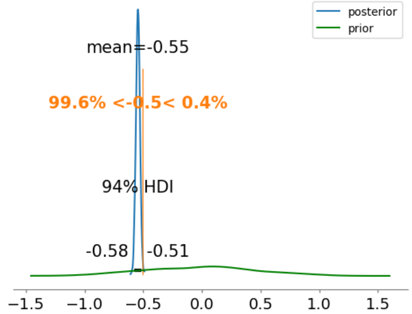
Table 3.1: Comparison of the prior and posterior predictive distributions using the two synthetic datasets

	Synthetic Data without Algorithm Aversion	Synthetic Data with Algorithm Aversion
Prior		
Posterior		

By comparing prior and posterior distributions, we assessed the model's ability to reproduce the intended relationships. As expected, when AA was absent (left column), there was no variation in ΔWTP across AIA levels. In contrast, when AA was present (right column), higher AIA levels (yellow) were associated with downward shifts in ΔWTP. This confirms that, as constructed, even when the AI-DST outperforms the human advisor ($\Delta Performance > 0$), AIA respondents prefer the human ($\Delta WTP < 0$).

To further evaluate whether our inference process can recover the "true" coefficients used to generate the data (γ_{AIA} and β_{AA}), we plotted the posterior distributions of these parameters for both datasets. Table 3.2 shows the posterior distributions for γ_{AIA} (top row) and β_{AA} (bottom row). The left column contains results for the dataset without AA, whereas the right column shows results for the dataset with AA.

Table 3.2: Comparison of prior, posterior, and set values for the coefficients of interest using the two datasets

	Synthetic Data without Algorithm Aversion	Synthetic Data with Algorithm Aversion
γ_{AIA}		
β_{AA}		

In each plot, the set values (i.e., 0 when AA is absent, and −0.5 when present) are marked in orange. Prior distributions are shown as green lines, and posterior distributions as blue lines. As the plots indicate, posterior estimates differ meaningfully from their priors and converge toward the values used to generate the synthetic data, confirming model functionality.

This stage of testing also led us to reflect on the experimental setup (e.g., how we elicited WTP values and randomized past correct recommendations). The full procedure described in Section 2.4, including code for data generation, simulation, and visualization, is documented in the pre-registration and available in the associated code repository.

As noted in the code repository,[§§] inferencing was conducted using a no-U-turn (NUTS) sampler Markov chain Monte Carlo (MCMC) approach with two chains. We generated 1,000 posterior samples per chain, following a 1,000-sample warm-up. The full workflow was implemented in Python

[§§] https://anonymous.4open.science/r/AlgorithmAversion_Public-5487/README.md (v3.12.4; Van Rossum & Drake, 2009) using NumPyro (v0.15.2; Phan et al., 2019; Bingham et al., 2019), and JAX (v0.4.31; Bradbury et al., 2018). Model performance was evaluated through inspection of trace plots for selected parameters, which confirmed successful convergence across both synthetic datasets (see Appendix B).

3.2.5 *Analysis of Real Data and Descriptive Statistics*

In the final step of the PP workflow, we analyzed the empirical data collected from the survey and experiment, using the same model specifications as defined and tested in the DGP. Importantly, the model was allowed to learn from the data and to update prior distributions accordingly. A summary table for the MCMC sampling procedure is provided in Appendix C.

As shown in Table 3.3, the 250 participating German arable farmers were, on average, slightly AI-anxious to AI-neutral. The median AIA score was 4 and the mean is 4.39 on a 7-point Likert scale. Participants reported an average WTP of 16 euro for advice from an AI-DST and 26 euro for advice from a human advisor. Notably, the maximum possible WTP of 150 euro was reached for the human advisor, but not for the AI-DST. The stated intention to adopt AI-DSTs was generally reserved, with a median of 4 on the same Likert scale. Respondents also reported moderate levels of risk tolerance—neither extremely risk-averse nor risk-seeking.[***]

Regarding representativeness, the sample aligned well with the German farming population in terms of age and production system. However, farms in the sample tended to be somewhat larger than the national average, likely due to the study's focus on crop producers. Unobserved variables may also

[***] We measured risk preferences using a self-assessment on an 11-point Likert-scale ranging from 0 ("Not at all willing to take risks") to 10 ("Very willing to take risks") based on the study by Dohmen et al. (2011) (see Appendix A for formulation of the respective question in the survey). While we are aware that self-assessment of risk preferences using the Dohmen-scale can be biased upwards compared to lottery-based assessment (Sauter, Hermann and Mußhoff 2018), we opted for this approach to reduce survey length and complexity.

influence sample representativity, and these limitations should be considered when interpreting results.

Table 3.3: Descriptive sample statistics and comparison to the German average

Variable	**Median / Frequency**	**Mean**	**Standard Deviation**	**Min**	**Max**	**German Average [a]**
Farm and farmer characteristics						
Age (in years)	55–64	49	12.22	21	76	55–64
Farm Size (in ha)						
< 5	0%					6%
5–9	1%					18%
10–19	7%					20%
20–49	21%					23%
50–99	28%					17%
100–199	26%					10%
200–499	10%					4%
500–999	2%					1%
1000 and more	4%					1%
Production system						
conventional	94%					89%
fully or partially organic	6%					11%
Risk Preference *(1= risk averse, 10 = risk loving)*	5	5.39	1.97	1	10	
DST Experience *(1 = very bad, 7 = excellent)*	5	4.44	1.69	1	7	
Advisor Experience *(1 = very bad, 7 = excellent)*	5	5.18	1.63	1	7	
UTAUT-Constructs [b, c]						
Technology Engagement	4	4.50	1.01	2	7	
Performance Expectancy	5	4.58	1.30	1	7	
Effort expectancy	5	4.89	1.29	1	7	
Social Influence	4	3.63	1.20	1	7	
Behavioral Intention	4	3.90	1.48	1	7	
AI-anxiety	4	4.39	1.15	1	7	
Willingness-To-Pay (in €)						
WTP for DST	10	16.31	20.16	0	115	
WTP for the human advisor	17	25.52	25.15	0	150	

[a] *DESTATIS* (2025)
[b] *"1 = totally disagree, 4 = indifferent, 7 = totally agree"* (see survey in Appendix A)
[c] Constructs based on the mean from several statements (see survey in Appendix A)

3.3 Results: Role of AA in Farmers' Decision Making

We estimated latent AIA for each individual across all posterior samples,[†††] using the model specified in Section 2.3; the distribution is shown in Fig. 3.6. The vast majority of farmers exhibit positive latent AIA, meaning they can be classified as "AI-anxious" (i.e., $Latent\ AIA > 0$).

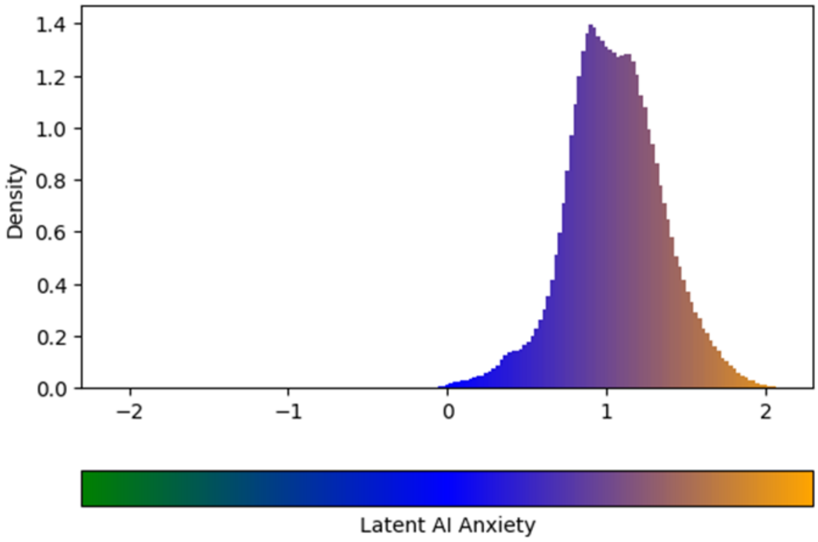


Figure 3.6: Distribution of latent AI-anxiety for all individuals across all posterior samples

To test our hypothesis that AA plays a role in farmers' decisions, we examine the effects of AIA on both BI and WTP. The coefficients of interest, γ_{AIA} and β_{AA}, were clearly negative. The mean of γ_{AIA} was –0.56 with a 90% highest posterior density interval (HPDI) of [–1.03; 0.00], whereas the mean of β_{AA} was –0.35 with a 90%-HPDI of [–0.40; –0.31]. The HPDI represents the narrowest interval containing the specified probability mass, such that any value outside the interval is less probable than any value within

[†††] This resulted in 241 * 2,000 observations. We excluded nine observations for the analysis where the base WTP of Human with 90% correct past performance is 0 (as it is not possible to divide by zero). Of those, seven were excluded as the farmers exhibited a WTP of 0 for all options. Further two observations are excluded as the WTPs are not logical: farmers have a WTP of 0 for a human with 90% past correct performance and WTPs > 0 for Human advice with 85% and 95% past correct performance.

it (Gelman et al., 2013; McElreath, 2018). A coefficient plot comparing prior and posterior distributions is provided in Appendix D. These results support our hypothesis that AA plays a role in farmers' intentions to adopt AI-DSTs.

Figure 3.7 shows the relationship between PE and BI (left panel, UTAUT model) and between $\Delta Performance$ and ΔWTP (right panel, experiment), across varying levels of latent AIA for each individual across all posterior samples. In both panels, higher levels of AIA (depicted in yellowish lines) are associated with downward shifts relative to AI-neutral individuals. To illustrate BI as a function of PE, we held other predictors (i.e., EE and SI) at their mean values. As shown in the left panel of Fig. 3.7, the baseline intention to adopt an AI-DST was relatively low, ceteris paribus. However, as PE increased, so did BI, indicating a positive relationship. The black line denotes an AI-neutral individual ($Latent\ AIA = 0$). Compared with this baseline, individuals with higher AIA exhibit lower BI at the same level of PE, as reflected in the downward shift of the yellowish lines and the negative value of $\gamma_{AIA} = -0.56$.

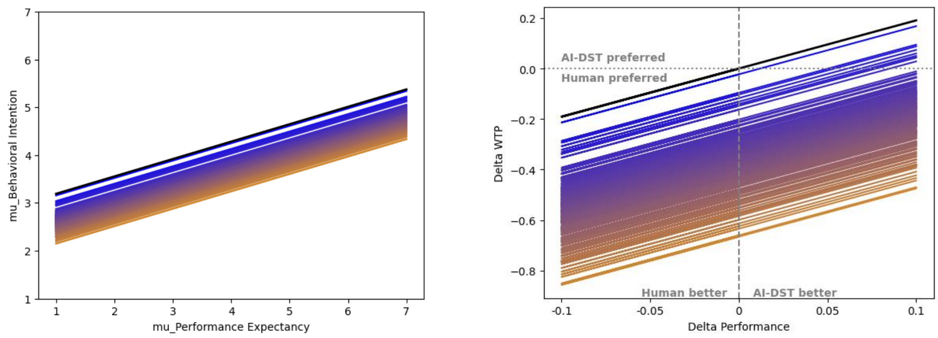


Figure 3.7: Average behavioral intention (left) and WTP (right) by given performance (expectancy) and latent AI-anxiety levels for all individuals across all posterior samples

The right panel of Fig. 3.7 shows ΔWTP as a function of $\Delta Performance$. Positive $\Delta Performance$ values indicate that the AI-DST outperforms the human advisor, whereas negative values favor the human. Similarly, positive ΔWTP values reflect a preference for the AI-DST, and negative values indicate a preference for the human. Again, the black line represents an AI-neutral individual ($Latent\ AIA = 0$). As expected, AI-neutral individuals prefer the advisor that performs better (i.e., human if $\Delta Performance < 0$ and AI-DST if $\Delta Performance > 0$).

In contrast, individuals with high AIA (yellowish lines) show consistently lower ΔWTP for the AI-DST, even when it performs equally well or better. This is captured in the negative coefficient, $\beta_{AA} = -0.35$, confirming that with increasing AIA, ΔWTP decreases. Thus, even when the AI-DST is superior, AI-anxious individuals remain willing to pay more for human advice, often placing them in the lower right quadrant of the plot.

Based on these findings, we computed the performance premium (i.e., the level by which the AI-DST must outperform the human advisor for a farmer to be equally willing to pay for both). This was done by solving the following equation, derived from Eq. (8), for each level of AIA to yield a distribution of performance premiums (see Fig. 3.8):

$$PerformancePremium = \frac{-\beta_{AA} * LatentAIAnxiety_i}{\beta_{DeltaPerformance}} \quad (18)$$

We found that, on average, the AI-DST would need to perform ~19% better than a human advisor to achieve equivalent WTP from farmers (mean = 0.195, median = 0.194). Beyond the average, it is instructive to consider the full distribution of the performance premium. For 90% of the posterior samples, the performance premium lies between 11% and 30% (90%- HPDI [0.110; 0.295]). This also implies that a small share of the posterior samples would prefer a human advisor over an AI-DST even if the performance of the human advisor is 30% lower. Another perspective on these results is the price premium (i.e., how much cheaper an AI-DST must be to be preferred over a human advisor when both perform equally). Assuming equal performance, we found that the AI-DST must be, on average, 37% less expensive. The 90% HPDI for this premium ranges [–0.56, –0.21], indicating that, for 90% of the posterior samples, the AI-DST must be between 21% and 56% cheaper than the human alternative.

In summary, both the overall BI to adopt AI-DSTs and the stated WTP for such tools were low across our sample. Even AI-neutral individuals appeared somewhat skeptical. However, the data clearly showed that AI-anxious individuals expressed significantly lower adoption intentions and WTP at given levels of (expected) performance. These results support our research hypothesis and affirm the role of AA in farmers' decision-making.

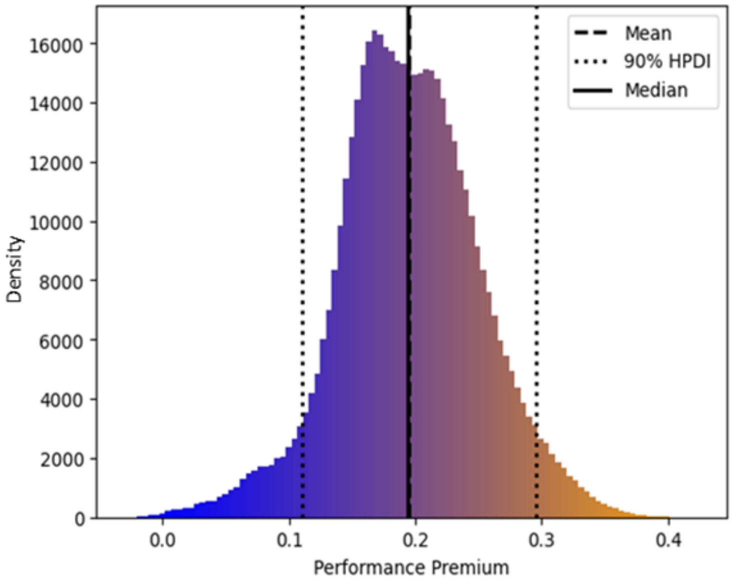


Figure 3.8: Distribution of performance premium

3.4 Discussion and Conclusion

3.4.1 *Comparing AA in the Agricultural Domain with Other Contexts*

When comparing our results to those of Longoni et al. (2019) in the medical domain, several similarities emerge. In their study, participants preferred human healthcare providers over AI-driven ones, even when the AI performed better; they were willing to pay more for human providers. Similarly, our findings revealed a clear price premium: on average, participants were willing to pay 37% less for AI-based advice, mirroring Longoni et al.'s (2019) result from Study 2, where WTP dropped by 37% when switching from human to AI support.

However, our observed performance premium (11–30%) diverged notably from Longoni et al.'s (2019) findings. In their Study 3 (Table 3), a mere 1% increase in accuracy was sufficient to overcome the utility gap between human and AI healthcare providers. By contrast, farmers in our sample required a much greater performance premium before expressing equal preference for AI. This discrepancy may stem from differences in experimental setup, cultural context, or decision-making environment—all of which have been shown to influence the magnitude of AA (Mahmud et al. 2022).

While Longoni et al.'s (2019) study is set in the medical context considering personal health risks, we focus on risks in agricultural decision making, where monetary aspects and external factors play a more pronounced role (Rosburg and Menapace 2018). Concretely, in the Longoni et al. (2019) –study, the 1%-point increase refers to the improvement of a medical diagnose, in our study it's about a 1%-point increase in the economic result. Studies on AA in the financial decision-making context found that risky environments lead people to reject even high performing algorithms and to overestimate mistakes made by the algorithm (Dietvorst and Bharti 2020; Zhang, Pentina and Fan 2021). As pesticide use is complex and the optimal application depends on many external factors like natural production conditions, weather and climate, infestation pressures and prices (Rosburg and Menapace 2018), this risk and uncertainty might foster AA among farmers in our sample compared to the sample of Longoni et al. (2019) and might explain the larger performance premium.

Our findings also align with psychological studies indicating that people lose trust in algorithmic forecasters more rapidly than in human ones, especially when performance imperfections are revealed (Dietvorst et al., 2015). This effect causes users to underestimate algorithmic accuracy and to avoid using algorithmic DS, even when it performs well (Dietvorst & Bharti 2020). Although we did not directly examine erroneous recommendations, our presentation of past correct recommendations implicitly conveys information about past errors. Future studies could explore whether the relationship between $\Delta Performance$ and ΔWTP is truly linear, as assumed here, or if it follows a nonlinear trajectory (e.g., disproportionately penalizing the AI-DST when its performance is slightly worse than that of the human advisor).

Regarding the UTAUT-based component of the model, our results are consistent with previous applications of this framework in agriculture, which also show a positive association between PE and BI (Otter & Deutsch, 2023; Von Veltheim et al., 2022; Giua et al., 2022; Michels et al., 2020). However, when comparing our findings to those of Cao et al. (2021), who extended UTAUT with AI-related constructs to measure UK business managers' intentions to use AI, the contrast is striking. While our German farmer sample reported a mean BI of 3.9, UK business managers reported a much higher mean of 5.14, both measured on a 7-point Likert scale. This difference suggests that German farmers may be more skeptical toward AI-based tools than decision-makers in other business sectors or regions.

3.4.2 *Reflecting on the PP Workflow*

The PP workflow adapted for the experimental setting (Fig. 3.1) offers several advantages. First, by defining a concrete DGP, we were required to explicitly and formally operationalize the concept of AA. Having a complete DGP also allowed us to create synthetic data to test this formalization. As depicted in Fig. 3.1, the development of the statistical model, experimental design, and variable operationalization occurred through an iterative loop. By using synthetic data, we could test various conceptual and experimental setups. This iterative workflow enabled us, for instance, to simulate different randomization strategies for past recommendation performance (with and without replacement) and to evaluate alternative functional forms between AIA and outcome variables. In both cases, we formulated and visualized a statistical model based on the scientific framework, adjusted the experimental design, generated synthetic data from the DGP, tested inference procedures, and assessed the results visually.

Second, this workflow helps identify and correct flaws in experimental design that might otherwise only become apparent after data collection. Because we can test both the survey and analysis pipeline in advance using synthetic data, we improve efficiency—saving time and resources—and enhance scientific rigor. This aligns with broader discussions on improving research practices (Ferraro & Shukla, 2023; Heckelei et al., 2023; Finger et al., 2023; 2024), including efforts toward pre-registration, registered reports (Arpinon & Lefebvre, 2024), and reproducibility through code sharing. By applying the PP workflow, we could pre-register the complete analysis pipeline, including code for data processing and results visualization, prior to collecting real data.

Third, from an empirical standpoint, the PP workflow enables the joint estimation of the key coefficients from both the WTP experiment and the UTAUT component. In both cases, AIA was treated as a shared latent driver of AA. A core strength of Bayesian inference is the ability to update prior beliefs with observed data. In our model, prior distributions for the parameters of interest were informed by the structure of the unified model and updated using the combined experimental and survey data. This joint estimation strategy improves precision and credibility of posterior results relative to methods that treat attitudinal and behavioral data separately.

One common critique of Bayesian approaches concerns the perceived subjectivity in the choice of priors. Generally, following McElreath (2018), we consider the prior specification as another part of the model assumptions. To motivate the chosen prior specification, we base it on: (i) using weakly informative priors, (ii) grounding our choices in prior literature, (iii) conducting prior predictive checks, and (iv) transparently documenting our choices and the rationale behind them. Besides the prior assumptions, it is also important to highlight that both the DAG and the DGP are based on a number of additional assumptions and represent just one of many plausible ways to construct the model. While the iterative development of DAG and DGP involves reflecting on and refining alternative structures, it is practically infeasible to test all possible configurations. However, this challenge is not unique to probabilistic programming, as any modeling approach is necessarily based on a specific set of assumptions.

3.4.3 *Potential Reasons for AA and Future Research Needs*

AA can be interpreted as a deviation from rational choice behavior. To understand and address this phenomenon, we integrate findings from AA literature in other domains with evidence on farmers' decision-making to identify future research directions.

A major barrier to adopting DSTs, particularly AI-based ones, is the lack of transparency (Rose et al., 2016; Kerebel et al., 2013; Akaka et al., 2024). The "black-box" nature of AI systems can limit user trust and understanding (Chander et al., 2018; Önkal et al., 2009). Additional concerns include the perception that AI may ignore local production conditions or fail to remain updated with evolving regulations (Rose et al., 2016). These concerns mirror the "uniqueness neglect" found in healthcare settings (Longoni et al., 2019) and are consistent with findings on the importance of localized learning in agricultural extension (Maertens et al., 2021; Oyinbo et al., 2022). Future research should explore how to enhance transparency, tailor recommendations to local contexts, clarify regulatory compliance, and address liability, potentially through pairing AI-DSTs with novel insurance mechanisms (Lefebvre et al., 2025).

However, increasing transparency can also raise system complexity, potentially exacerbating AA (You et al., 2022). Farmers thus face an "adopter's dilemma": balancing better recommendations against more complicated decision-making processes (McRoberts et al., 2011). Identifying the specific types of information farmers find most relevant may help mitigate this tension (Rojo-Gimeno et al., 2019; Helps et al., 2024; Sperber et al., 2010). Furthermore, research shows that the framing of AI recommendations (e.g., emphasizing gains vs. losses) can shape trust (Mahmud et al., 2022), and that the delivery mode (e.g., video or SMS) affects how farmers respond (Van Campenhout et al., 2021; Giulivi et al., 2023).

Like findings in healthcare and business, AA tends to rise with perceived task risk (Longoni et al., 2019; Filiz et al., 2023). In agriculture, risk framing might influence decision-making (Bougherara et al., 2024), and novel insurance schemes could support DST adoption (Lefebvre et al., 2025). Future work should investigate how AA varies across decision types (e.g., tactical vs. strategic) and time horizons.

More broadly, studies consistently find that farmers are cautious toward new technologies (Rose et al., 2016; Heidrich, 2020; McCown, 2002; Rojo-Gimeno et al., 2019; Akaka et al., 2024). In our sample, most farmers reported low technological interest, which aligns with evidence linking low tech engagement to reduced DST adoption (Von Veltheim et al., 2022). In other domains, AA has been shown to vary with user experience (Mahmud et al., 2022), which might be also the case for farmers. For instance, McFadden et al. (2022) found that digital soil mapping adoption declines with farmer age, whereas Gars et al. (2025) found that farmers with less confidence in their own fertilizer beliefs are more responsive to recommendations and exhibit higher WTP for new soil testing tools. Prior research suggests that customizability of algorithms can increase adoption (Logg et al., 2019; Önkal et al., 2009; Dietvorst et al., 2018). Future studies should examine how to incorporate farmer expertise into AI-DST outputs to boost acceptance (Hochman & Carberry, 2011).

Human advisors remain influential in agricultural decision-making (Skaalsveen et al., 2020; Kuehne et al. 2020). In our study, most farmers rated their advisors highly, and AIA increased with advisor satisfaction ($\beta_{\mathrm{AdvisorExperience}_{\mathrm{AIA}}}$ in Table 3.4). This suggests that farmers may fear AI-DSTs could replace, rather than complement, trusted relationships (Rose et al., 2016; McCown, 2002), as has been observed in healthcare (Longoni et al., 2019). Future research should evaluate hybrid systems where human advisors interpret AI outputs before presenting them to farmers (Rojo-Gimeno et al., 2019), which may also serve as training opportunities for farmers. Notably, digital experience was associated with lower AIA in our sample ($\beta_{\mathrm{DSTExperience}_{\mathrm{AIA}}}$ in Table 3.4), underscoring the importance of digital literacy—particularly for older farmers, who often report lower digital confidence (Von Veltheim et al., 2022).

Lastly, peer opinions may also shape AA. In our study, most farmers believed that their peers did not support AI-DST use for fungicide application. This belief was associated with lower adoption intention ($\beta_{\mathrm{SI}_{\mathrm{BI}}}$ in Table 3.4). Farmers may fear that using AI-DSTs could damage their reputation for competence. Experimental studies confirm that users of algorithms are sometimes perceived as less capable (Diab et al., 2011;

Eastwood et al., 2012). Because farmers seek not only profit but also social validation (Weersink & Fulton, 2020), peer norms and recognition may significantly influence technology adoption. Future research should explore how social norms, such as peer effects can facilitate broader AI-DST use. For example, Alexander et al. (2018) showed that social proof is more persuasive in promoting algorithm adoption than presenting a specific accuracy level.

3.4.4 *Concluding Remarks*

AI-based DSTs hold considerable promise for improving productivity and resource use efficiency in agriculture. However, adoption remains a prerequisite for realizing this potential. In various domains, individuals show reluctance towards AI-based recommendations, known as algorithm aversion (Dietvorst et al. 2015). This study is the first to investigate and quantify AA in the agricultural context. We conducted an online survey of German arable farmers using a combination of UTAUT-based attitudinal measures and a controlled experiment to examine and quantify AA, that is the effect of AI-Anxiety on adoption intention and WTP, respectively. We also introduced and discussed a novel PP workflow to complement survey design, model testing, and inference transparency.

Our results confirmed that AA plays an important role in both stated BI and economic preference (WTP). As AIA increases, both adoption intention and WTP decline, validating our hypothesis. Based on our model and experimental setup, we estimated that an AI-DST must perform between 11% and 30% better than a human advisor, or cost between 21% and 56% less, to be considered equally valuable by most farmers.

AA could impose costs not only on individual farmers but also on broader society, especially if algorithms consistently outperform human recommendations (Dietvorst et al., 2015). Given the increasing potential of AI-based DST for efficiency improvements in agricultural production, future research should extend this framework to other adoption decisions and explore the causes of AA to develop effective interventions, including financial support mechanisms.

We recommend incorporating AIA as a dispositional factor in future behavioral research on farmers’ attitude towards AI, for example within the framework proposed by Déssart et al. (2019). Although our study relies on hypothetical scenarios, which may inflate WTP estimates (Veettil et al., 2024), we used established methods including a cheap talk script to mitigate such effects. As AI-DSTs become more widespread, future research should focus on revealed preferences in real-world settings.

Finally, technology developers should design AI-DSTs with AA in mind. Given the importance of performance perceptions and performance premiums, tools must communicate value clearly and transparently. Farmers’ risk perceptions also matter. Insurance schemes that compensate for yield loss when DST guidance is followed (Lefebvre et al., 2025; BASF, 2024) may provide a promising complement. AI should not aim to replace human advisors but to support and enhance human expertise (Evans et al., 2017; Hochman & Carberry, 2011; Rose et al., 2016). Given the strong preference for human input, advisory services should carefully assess which tasks can be delegated to AI and which are best retained by humans or pursued collaboratively.

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3.5 References

Literature7 U.S. Code § 136r-1. 2018. “Integrated Pest Management.” *“7 U.S. Code § 136r-1.”* Available at: https://www.law.cornell.edu/uscode/text/7/136r-1.

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

Alexander, V., C. Blinder, and P.J. Zak. 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.

Andrich, D. 2005. “The Rasch Model Explained.” In *Education in the Asia-Pacific Region: Issues, Concerns and Prospects*. Berlin/Heidelberg: Springer-Verlag, pp. 27–59.

Angrist, J.D., and J.-S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton University Press.

Arpinon, T., and M. Lefebvre. 2024. “Registered reports and associated benefits for agricultural economics.” *Q open*. Available at: http://dx.doi.org/10.1093/qopen/qoae011.

BASF. 2024. “xarvio HEALTHY FIELDS.” Available at: https://www.xarvio.com/de/de/products/healthy-fields.html [Accessed January 9, 2025].

Bessette, D., R. Wilson, C. Beaudrie, and C. Schroeder. 2019. “An online decision support tool to evaluate ecological weed management strategies.” *Weed Science* 67(4):463–473.

Bingham, E., J.P. Chen, M. Jankowiak, F. Obermeyer, N. Pradhan, T. Karaletsos, R. Singh, P.A. Szerlip, P. Horsfall, and N.D. Goodman. 2019. “Pyro: Deep Universal Probabilistic Programming.” *J. Mach. Learn. Res.* 20:28:1-28:6.

Bradbury, J., R. Frostig, P. Hawkins, M.J. Johnson, C. Leary, D. Maclaurin, G. Necula, A. Paszke, J. VanderPlas, S. Wanderman-Milne, and Q. Zhang. 2018. *JAX: composable transformations of Python+NumPy programs*. Available at: http://github.com/jax-ml/jax.

Bürkner, P.-C., and M. Vuorre. 2019. “Ordinal regression models in psychology: A Tutorial.” *Advances in methods and practices in psychological science* 2(1):77–101.

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

CBD. 2025. “2030 targets (with guidance notes).” *“Convention on Biological Diversity.”* Available at: https://www.cbd.int/gbf/targets [Accessed April 23, 2025].

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

Chatzimichael, K., M. Genius, and V. Tzouvelekas. 2022. “Pesticide use, health impairments and economic losses under rational farmers behavior.” *American journal of agricultural economics* 104(2):765–790.

Cohen, S.N., D. Snow, and L. Szpruch. 2021. “Black-box model risk in finance.” *arXiv [q-fin.CP]*. Available at: http://arxiv.org/abs/2102.04757.

De la Peña, N., and O.M. Granados. 2024. “Artificial intelligence solutions to reduce information asymmetry for Colombian cocoa small-scale farmers.” *Information processing in agriculture* 11(3):310–324.

Déssart, F.J., J. Barreiro-Hurlé, and R. van Bavel. 2019. “Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review.” *European Review of Agricultural Economics* 46(3):417–471.

DESTATIS. 2025. “Landwirtschaftszählung: Haupterhebung.” *Landwirtschaftszählung: Haupterhebung*. Available at: https://www-genesis.destatis.de/datenbank/online/statistic/41141/details [Accessed February 18, 2025].

Diab, D.L., S.-Y. Pui, M. Yankelevich, and S. Highhouse. 2011. "Lay perceptions of selection decision aids in US and non-US samples." *International journal of selection and assessment* 19(2):209–216.

Dietvorst, B.J., and S. Bharti. 2020. "People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error." *Psychological science* 31(10):1302–1314.

Dietvorst, B.J., J.P. Simmons, and C. Massey. 2015. "Algorithm aversion: people erroneously avoid algorithms after seeing them err." *Journal of experimental psychology. General* 144(1):114–126.

Dietvorst, B.J., J.P. Simmons, and C. Massey. 2018. "Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them." *Management science* 64(3):1155–1170.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G.G. Wagner. 2011. "Individual Risk Attitudes: Measurement, Determinants, and Behavioral Consequences." *Journal of the European Economic Association* 9(3):522–550.

Eastwood, J., B. Snook, and K. Luther. 2012. "What people want from their professionals: Attitudes toward decision-making strategies." *Journal of behavioral decision making* 25(5):458–468.

European Commission. 2024a. "Integrated pest management (IPM)." *Food Safety*. Available at: https://food.ec.europa.eu/plants/pesticides/sustainable-use-pesticides/integrated-pest-management-ipm_en [Accessed November 12, 2024].

European Commission. 2020. "Key policy objectives of the CAP 2023-27." *Agriculture and rural development*. Available at: https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cap-2023-27/key-policy-objectives-cap-2023-27_en [Accessed December 5, 2024].

European Commission. 2024b. "REGULATION (EU) 2024/1689 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL laying down harmonised rules on artificial intelligence." Available at:

https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=OJ:L_202401689 [Accessed March 12, 2025].

Eurostat. 2024. “Pesticide sales.” Available at: http://dx.doi.org/10.2908/aei_fm_salpest09CopyDOIURL [Accessed May 12, 2024].

Evans, K.J., A. Terhorst, and B.H. Kang. 2017. “From Data to Decisions: Helping Crop Producers Build Their Actionable Knowledge.” *Critical reviews in plant sciences* 36(2):71–88.

FAO. 2024. “Crops and livestock products - Export quantity.” *Trade / Crops and livestock products*. Available at: https://www.fao.org/faostat/en/#data/TCL [Accessed April 23, 2025].

Ferraro, P.J., and P. Shukla. 2023. “Credibility crisis in agricultural economics.” *Applied economic perspectives and policy* 45(3):1275–1291.

Figueroa, M., K.E. Hammond-Kosack, and P.S. Solomon. 2018. “A review of wheat diseases—a field perspective.” *Molecular plant pathology* 19(6):1523–1536.

Finger, R., C. Grebitus, and A. Henningsen. 2023. “Replications in agricultural economics.” *Applied economic perspectives and policy* 45(3):1258–1274.

Finger, R., A. Henningsen, J. Höhler, R. Huber, J. Rommel, and C. Grebitus. 2024. “Open science in agricultural economics.” *Q open*. Available at: http://dx.doi.org/10.1093/qopen/qoae029.

Finger, R., S.M. Swinton, N. El Benni, and A. Walter. 2019. “Precision Farming at the Nexus of Agricultural Production and the Environment.” *Annual Review of Resource Economics* 11(1):313–335.

Fox, J.-P. 2010. *Bayesian item response modeling* 2010th ed. New York, NY: Springer. Available at: https://books.google.at/books?id=BZcPc4ffSTEC.

Fritsch, C., P. Berny, O. Crouzet, S. Le Perchec, and M. Coeurdassier. 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*. Available at: http://dx.doi.org/10.1007/s11356-024-33026-1.

Gars, J., R. Fishman, A. Kishore, Y. Rothler, and P.S. Ward. 2025. "Confidence and information usage: Evidence from soil testing in India." *American journal of agricultural economics*. Available at: http://dx.doi.org/10.1111/ajae.12513.

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

Geiger, F., J. Bengtsson, F. Berendse, W.W. Weisser, M. Emmerson, M.B. Morales, P. Ceryngier, J. Liira, T. Tscharntke, C. Winqvist, S. Eggers, R. Bommarco, T. Pärt, V. Bretagnolle, M. Plantegenest, L.W. Clement, C. Dennis, C. Palmer, J.J. Oñate, I. Guerrero, V. Hawro, T. Aavik, C. Thies, A. Flohre, S. Hänke, C. Fischer, P.W. Goedhart, and P. Inchausti. 2010. "Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland." *Basic and applied ecology* 11(2):97–105.

Gelman, A., J.B. Carlin, H.S. Stern, D.B. Dunson, A. Vehtari, and D.B. Rubin. 2013. *Bayesian data analysis, third edition* 3rd ed. Philadelphia, PA: Chapman & Hall/CRC. Available at: https://sites.stat.columbia.edu/gelman/book/BDA3.pdf.

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

Gianessi, L., and A. Williams. 2011. "Europe's wheat yields are the world's highest due to fungicide use." Available at: https://croplife.org/wp-content/uploads/pdf_files/Europes-wheat-yields-are-the-worlds-highest-due-to-fungicide-use.pdf.

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

Giulivi, N., A.P. Harou, S. Gautam, and D. Guereña. 2023. “Getting the message out: Information and communication technologies and agricultural extension.” *American journal of agricultural economics* 105(3):1011–1045.

Heckelei, T., S. Hüttel, M. Odening, and J. Rommel. 2023. “The p-value debate and statistical (Mal)practice – implications for the agricultural and food economics community.” *German journal of agricultural economics* 72(1):47–67.

Heidrich, S.W. 2020. *Akzeptanz einer On-Line Anwendung zur landwirtschaftlichen Betriebsoptimierung als Entscheidungshilfe*. Bachelor. RHEINISCHE FRIEDRICH-WILHELMS-UNIVERSITÄT BONN .

Helps, J.C., F. van den Bosch, N. Paveley, L.N. Jørgensen, N. Holst, and A.E. Milne. 2024. “A framework for evaluating the value of agricultural pest management decision support systems.” *European journal of plant pathology* 169(4):887–902.

Henningsen, A., G. Low, D. Wuepper, T. Dalhaus, H. Storm, D. Belay, and S. Hirsch. 2024. “Estimating causal effects with observational data: Guidelines for agricultural and applied economists.” *University of Copenhagen, Department of Food and Resource Economics (IFRO), Copenhagen*. Available at: https://hdl.handle.net/10419/308008.

Hochman, Z., and P.S. Carberry. 2011. “Emerging consensus on desirable characteristics of tools to support farmers’ management of climate risk in Australia.” *Agricultural systems* 104(6):441–450.

Hossain, L., R. Rahman, and M.S. Khan. 2017. “Alternatives of Pesticides.” In M. S. Khan and M. S. Rahman, eds. *Pesticide Residue in Foods: Sources, Management, and Control*. Cham: Springer International Publishing, pp. 147–165.

Huntington-Klein, N. 2021. *The effect: An introduction to research design and causality*. London, England: Taylor & Francis. Available at: https://theeffectbook.net/ [Accessed April 23, 2025].

Imbens, G.W. 2020. “Potential outcome and directed acyclic graph approaches to causality: Relevance for empirical practice in economics.” *Journal of Economic Literature* 58(4):1129–1179.

Jarrahi, M.H., C. Lutz, K. Boyd, C. Oesterlund, and M. Willis. 2022. "Artificial intelligence in the work context." *Journal of the Association for Information Science and Technology*. Available at: http://dx.doi.org/10.1002/asi.24730.

Johnson, D.G., and M. Verdicchio. 2017. "AI Anxiety." *Journal of the Association for Information Science and Technology* 68(9):2267–2270.

Kaplan, A.D., T.T. Kessler, J.C. Brill, and P.A. Hancock. 2023. "Trust in Artificial Intelligence: Meta-Analytic Findings." *Human factors* 65(2):337–359.

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

Khanna, M., S.S. Atallah, T. Heckelei, L. Wu, and H. Storm. 2024. "Economics of the Adoption of Artificial Intelligence–Based Digital Technologies in Agriculture." Available at: https://www.annualreviews.org/content/journals/10.1146/annurev-resource-101623-092515 [Accessed July 29, 2024].

Kiraly, G., S. Vago, E. Bull, L. van der Cruyssen, T. Arbour, P. Spanoghe, and L. van DIJK. 2023. "Information behaviour of farmers, foresters, and advisors in the context of digitalisation in the EU." *Studies.hu*. Available at: https://studies.hu/information-behaviour-of-farmers-foresters-and-advisors-in-the-context-of-digitalisation-in-the-eu/ [Accessed February 26, 2024].

Krishnan, P., and M. Patnam. 2014. "Neighbors and extension agents in Ethiopia: Who matters more for technology adoption?" *American journal of agricultural economics* 96(1):308–327.

Kuehne, G., R. Nettle, R. Llewellyn, and G. Osmond. 2020. "Key social processes sustaining the farmer/advisor relationship." Available at: https://search.informit.org/doi/abs/10.3316/INFORMIT.940449029694795.

Landwirtschaftskammer, N.R.W. 2024. "Beratung Ackerbau und Grünland." *https://www.landwirtschaftskammer.de/*. Available at: https://www.landwirtschaftskammer.de/landwirtschaft/ackerbau/beratung/index.htm [Accessed December 3, 2025].

Läpple, D., and B.L. Barham. 2019. "How do learning ability, advice from experts and peers shape decision making?" *Journal of Behavioral and Experimental Economics* 80:92–107.

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

Lefebvre, M., Y. Raineau, C. Aubert, N. Möhring, P. Pedehour, and M. Raynal. 2025. "Green insurance for pesticide reduction: Acceptability and impact for French viticulture." *European review of agricultural economics*. Available at: http://dx.doi.org/10.1093/erae/jbaf002.

Leyens, A.F., J. Philipp Börner, M. Hartmann, and H. Storm. 2024. "Round effects in economic experiments - A novel probabilistic programming approach to timevariant response behaviour." In *Agricultural Economics Society - AES > 98th Annual Conference, March 18-20, 2024, The University of Edinburgh, Edinburgh, UK*. AgEcon Search. Available at: https://ageconsearch.umn.edu/record/355341.

Liddell, T.M., and J.K. Kruschke. 2018. "Analyzing ordinal data with metric models: What could possibly go wrong?" *Journal of experimental social psychology* 79:328–348.

Logg, J.M., J.A. Minson, and D.A. Moore. 2019. "Algorithm appreciation: People prefer algorithmic to human judgment." *Organizational behavior and human decision processes* 151:90–103.

Longoni, C., A. Bonezzi, and C.K. Morewedge. 2019. "Resistance to Medical Artificial Intelligence." *The Journal of consumer research* 46(4):629–650.

Maertens, A., H. Michelson, and V. Nourani. 2021. "How do farmers learn from extension services? Evidence from Malawi." *American journal of agricultural economics* 103(2):569–595.

Mahmud, H., A.K.M.N. Islam, S.I. Ahmed, and K. Smolander. 2022. "What influences algorithmic decision-making? A systematic literature review on algorithm aversion." *Technological forecasting and social change* 175:121390.

Malle, B.F. 2011. “Attribution theories: how people make sense behavior.” In D. Chadee, ed. *Theories Social Psychology*. Wiley-Blackwell, pp. 72–95.

McCown, R.L. 2002. “Changing systems for supporting farmers’ decisions: problems, paradigms, and prospects.” *Agricultural systems* 74(1):179–220.

McElreath, R. 2018. *Statistical rethinking: A Bayesian course with examples in R and Stan*. Chapman and Hall/CRC.

McFadden, J.R., A. Rosburg, and E. Njuki. 2022. “Information inputs and technical efficiency in midwest corn production: evidence from farmers’ use of yield and soil maps.” *American journal of agricultural economics* 104(2):589–612.

McMahon, T.A., N.T. Halstead, S. Johnson, T.R. Raffel, J.M. Romansic, P.W. Crumrine, and J.R. Rohr. 2012. “Fungicide-induced declines of freshwater biodiversity modify ecosystem functions and services.” *Ecology letters* 15(7):714–722.

McRoberts, N., C. Hall, L.V. Madden, and G. Hughes. 2011. “Perceptions of disease risk: from social construction of subjective judgments to rational decision making.” *Phytopathology* 101(6):654–665.

Michels, M., V. Bonke, and O. Musshoff. 2020. “Understanding the adoption of smartphone apps in crop protection.” *Precision Agriculture* 21(6):1209–1226.

Möhring, N., D. Wuepper, T. Musa, and R. Finger. 2020. “Why farmers deviate from recommended pesticide timing: the role of uncertainty and information.” *Pest management science* 76(8):2787–2798.

Oerke, E.-C. 2006. “Crop losses to pests.” *The Journal of agricultural science* 144(1):31–43.

Önkal, D., P. Goodwin, M. Thomson, S. Gönül, and A. Pollock. 2009. “The relative influence of advice from human experts and statistical methods on forecast adjustments.” *Journal of behavioral decision making* 22(4):390–409.

Orn, D., L. Duan, Y. Liang, H. Siy, and M. Subramaniam. 2020. “Agro-AI education: Artificial intelligence for future farmers.” In *Proceedings of the 21st Annual Conference on Information*

Technology Education. SIGITE ’20: The 21st Annual Conference on Information Technology Education. New York, NY, USA: ACM. Available at: https://dl.acm.org/doi/abs/10.1145/3368308.3415457.

Otter, V., and M. Deutsch. 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.

Oyinbo, O., J. Chamberlin, T. Abdoulaye, and M. Maertens. 2022. “Digital extension, price risk, and farm performance: experimental evidence from Nigeria.” *American journal of agricultural economics* 104(2):831–852.

Pearl, J., and D. Mackenzie. 2018. *The book of why: the new science of cause and effect*. Basic Books, New York. ISBN 9780465097609: Springer Science and Business Media LLC.

Phan, D., N. Pradhan, and M. Jankowiak. 2019. “Composable Effects for Flexible and Accelerated Probabilistic Programming in NumPyro.” *arXiv preprint arXiv:1912. 11554*.

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

Rosburg, A., and L. Menapace. 2018. “Factors influencing corn fungicide treatment decisions.” *of agricultural and resource …*. Available at: https://ageconsearch.umn.edu/record/273444/.

Rose, D.C., C. Parker, J. Fodery, C. Park, W.J. Sutherland, and L.V. Dicks. 2018. “Involving stakeholders in agricultural decision support systems: Improving user-centred design.” *International Journal of Agricultural Management* 06(3–4). Available at: https://ideas.repec.org/a/ags/ijameu/287292.html [Accessed January 11, 2024].

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." *Agricultural systems* 149:165–174.

Rübcke von Veltheim, F., L. Theuvsen, and H. Heise. 2022. "German farmers' intention to use autonomous field robots: a PLS-analysis." *Precision Agriculture* 23(2):670–697.

Sauter, P.A., D. Hermann, and O. Mußhoff. 2018. "Are foresters really risk-averse? A multi-method analysis and a cross-occupational comparison." *Forest policy and economics* 95:37–45.

Schneider, K., J. Barreiro-Hurle, and E. Rodriguez-Cerezo. 2023. "Pesticide reduction amidst food and feed security concerns in Europe." *Nature Food* 4(9):746–750.

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

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

Skevas, T., S.E. Stefanou, and A. Oude Lansink. 2014. "Pesticide use, environmental spillovers and efficiency: A DEA risk-adjusted efficiency approach applied to Dutch arable farming." *European journal of operational research* 237(2):658–664.

Smith, R., and R. Van den Bosch. 1967. "Integrated control." *Pest control: biological, physical and selected chemical methods*:295–340.

Sperber, D., F. Clément, C. Heintz, O. Mascaro, H. Mercier, G. Origgi, and D. Wilson. 2010. "Epistemic vigilance." *Mind & language* 25(4):359–393.

Spielman, D., E. Lecoutere, S. Makhija, and B. Van Campenhout. 2021. "Information and communications technology (ICT) and agricultural extension in developing countries." *Annual review of resource economics* 13(1):177–201.

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

Storm, H., S.J. Seidel, L. Klingbeil, F. Ewert, H. Vereecken, W. Amelung, S. Behnke, M. Bennewitz, J. Börner, T. Döring, J. Gall, A.-K. Mahlein, C. McCool, U. Rascher, S. Wrobel, A. Schnepf, C. Stachniss, and H. Kuhlmann. 2024. "Research priorities to leverage smart digital technologies for sustainable crop production." *European journal of agronomy: the journal of the European Society for Agronomy* 156(127178):127178.

Stranieri, S., A. Varacca, M. Casati, E. Capri, and C. Soregaroli. 2022. "Adopting environmentally-friendly certifications: transaction cost and capabilities perspectives within the Italian wine supply chain." *Supply Chain Management: An International Journal* 27(7):33–48.

USDA. 2025. "Natural Resources Conservation Service." Available at: https://www.nrcs.usda.gov/ [Accessed April 23, 2025].

USDA NIFA. 2025. "Crop Protection and Pest Management program." *National Institute of Food and Agriculture*. Available at: https://www.nifa.usda.gov/grants/programs/crop-protection-pest-management-program [Accessed April 23, 2025].

Van Campenhout, B., D.J. Spielman, and E. Lecoutere. 2021. "Information and communication technologies to provide agricultural advice to smallholder farmers: Experimental evidence from Uganda." *American journal of agricultural economics* 103(1):317–337.

Van Rossum, G., and F.L. Drake. 2009. *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace.

Varacca, A. 2024. "Latently mediating: A Bayesian take on causal mediation analysis with structured survey data." *Multivariate behavioral research*:1–23.

Veettil, P.C., Y. Yashodha, and J. Vecci. 2024. "Hypothetical bias and cognitive ability: Farmers' preference for crop insurance products." *American journal of agricultural economics*. Available at: https://onlinelibrary.wiley.com/doi/10.1111/ajae.12506.

Venkatesh, V. 2000. "Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model." *Information Systems Research* 11(4):342–365.

Venkatesh, V., M.G. Morris, G.B. Davis, and F.D. Davis. 2003. “User Acceptance of Information Technology: Toward a Unified View.” *The Mississippi quarterly* 27(3):425–478.

Walter, A., R. Finger, R. Huber, and N. Buchmann. 2017. “Opinion: Smart farming is key to developing sustainable agriculture.” *Proceedings of the National Academy of Sciences of the United States of America* 114(24):6148–6150.

Wang, Y.-Y., and Y.-S. Wang. 2022. “Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior.” *Interactive Learning Environments* 30(4):619–634.

Weersink, A., and M. Fulton. 2020. “Limits to Profit Maximization as a Guide to Behavior Change.” *Applied Economic Perspectives and Policy* 42(1):67–79.

Workman, M. 2005. “Expert decision support system use, disuse, and misuse: a study using the theory of planned behavior.” *Computers in human behavior* 21(2):211–231.

You, S., C.L. Yang, and X. Li. 2022. “Algorithmic versus human advice: Does presenting prediction performance matter for algorithm appreciation?” *Journal of management information systems : JMIS* 39(2):336–365.

Yousaf, A., V. Kayvanfar, A. Mazzoni, and A. Elomri. 2023. “Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions.” *Frontiers in sustainable food systems* 6. Available at: https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2022.1053921/full.

Zhang, L., I. Pentina, and Y. Fan. 2021. “Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services.” *Journal of services marketing* 35(5):634–646.

3.6 Appendix

3.6.1 *A. Survey*

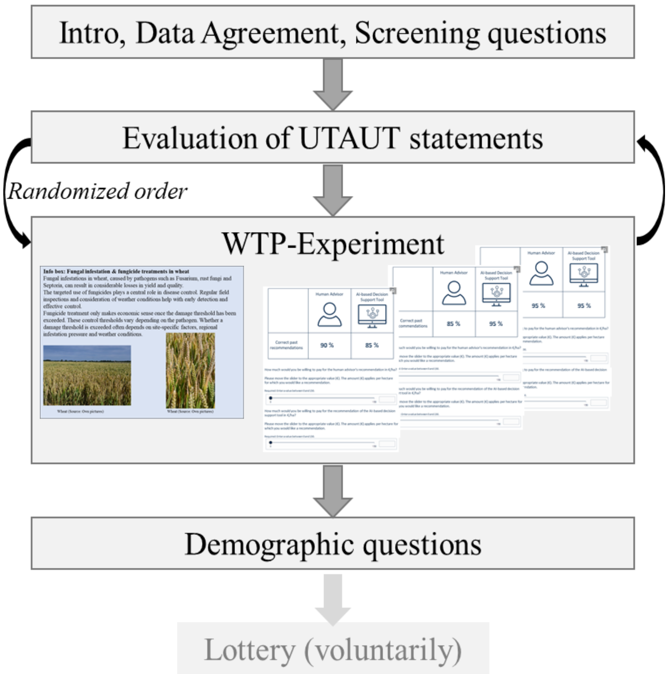


Figure 3.9: Schematic Process of the survey

Decision Support Tools in Crop Management

In this study, we want to investigate the extent to which digital decision support tools are used in arable farming.

Many decisions have to be made in everyday agricultural work. Apps for detecting and treating weeds, recommending fungicide treatments or digital field maps can help to optimize decisions.

To do this, these programs evaluate large amounts of data in order to provide up-to-date recommendations adapted to the location. In the future, these techniques will increasingly use artificial intelligence (AI) to make optimal predictions and recommendations based on the available data.

In the following, we use the term “AI-based decision support” for any type of technology that evaluates mathematical correlations without human intervention and formulates recommendations based on this.

The study takes about 18 minutes. At the end, you can decide whether you would like to take part in a lottery and receive the results of the study as a thank you for your participation.

We are giving away a total of four non-cash prizes among all participants:

[list of prizes in kind]

To get started, please agree to the data protection guidelines.

Thank you for participating in the study.

- ○ I agree.
- ○ I do not agree. (→ Screenout)

Branches of operation/ Screenout:

Which branches of business belong to the company?

(multiple answers possible)

- ○ Arable farming / market crops → Continue in the questionnaire
- ○ Forage production → Screenout
- ○ Special crops (e.g. fruit and vegetables) → Screenout
- ○ Permanent crop area (e.g. hops) → Screenout
- ○ Animal production / processing → Screenout
- ○ Renewable energies → Screenout
- ○ Forestry → Screenout
- ○ Aquaculture → Screenout
- ○ Secondary production (e.g. farm store) → Screenout
- ○ Other, namely: ___ → Screenout

[From here on randomized: order of statements, experiment and ranking]

Part 1: Evaluation of statements

In the following, we will show you several statements on the topic of decision support for fungicide strategy planning. Please rate the extent to which you agree with the statements.

You can use the scale to grade your statement from 1 “strongly disagree” to 7 “strongly agree”.

[Part 1.1: Fungicide treatment]

- I would find the use of AI-based decision support for fungicide applications useful in my day-to-day work. *[PE 1]*
- I think that the use of an AI-based decision aid for fungicide applications would reduce my workload. *[PE 2]*
- I think that using an AI-based decision aid for fungicide applications would reduce my crop protection costs. *[PE 3]*
- I think that AI-based decision support for fungicide applications would help to make crop protection more environmentally friendly. *[PE 4]*
- I think that using an AI-based decision aid for fungicide applications would be easy for me to learn. *[EE 1]*
- After learning to use an AI-based decision aid for fungicide applications, it would be easy and understandable for me to use. *[EE 2]*
- I think that an AI-based decision aid for fungicide applications would be an easy-to-use aid for me. *[EE 3]*
- My work colleagues think that I should use an AI-based decision aid for fungicide applications. *[SI 1]*
- Farmer friends think it makes sense to use an AI-based decision aid for fungicide applications. *[SI 2]*
- I specifically intend to use AI-based decision support for fungicide applications in the near future. *[BI 1]*
- I plan to use AI-based decision support for fungicide applications in the medium term. *[BI 2]*
- I suspect that I will use AI-based decision support for fungicide applications in the long term. *[BI 3]*
- I plan to use non-AI-based digital decision aids in the future.

[Part 1.2: Artificial intelligence]

In the following, we will show you several statements on the topic of AI techniques (artificial intelligence). These relate to areas both within and outside agriculture.

Examples of AI technologies include chatbots such as ChatGPT, voice assistants such as Siri or Alexa, automatic facial recognition for unlocking cell phones, parking aids in cars and suggestions on YouTube based on previously watched videos.

Please rate the extent to which you agree with the statement. You can use the scale to grade your statement from 1 "Strongly disagree" to 7 "Strongly agree".

- I am afraid that AI technologies could make society dependent. *[AIA 1]*
- I am afraid that AI technologies could make society lazier. *[AIA 2]*
- I am afraid that AI technologies could replace humans. *[AIA 3]*
- I am afraid that the widespread use of AI technologies could take jobs away from people. *[AIA 4]*
- I find human-like AI technologies (e.g. human-like robots) strange. *[AIA 5]*
- I don't know why, but human-like AI technologies (e.g. human-like robots) scare me. *[AIA 6]*
- I am afraid that if I start using AI techniques, I will lose some of my ability to think. *[AIA 7]*
- I am afraid that AI techniques could be misused for harmful purposes. *[AIA 8]*
- I am afraid of various problems that could be associated with AI techniques. *[AIA 9]*
- I am afraid that AI technologies will get out of control and nothing will work anymore. *[AIA 10]*
- I am afraid that AI techniques could lead to the autonomy of robots. *[AIA 10]*
- Learning all the special functions that come with an AI technique makes me nervous. *[AIA 12]*
- Learning how to use AI techniques makes me anxious. *[AIA 13]*
- Learning how to interact with AI techniques makes me anxious. *[AIA 14]*
- Taking a course on the development of AI techniques worries me. *[AIA 15]*
- Not being able to keep up with advances related to AI techniques worries me. *[AIA 16]*

Part 2: Advisory services

Below you will find information on two advisory options for fungicide applications. Please put yourself in the situation described below and read through the information on fungal infestation in wheat and possible recommendations for measures and fungicide treatments:

Info box: Fungal infestation & fungicide treatments in wheat

Fungal infestations in wheat, caused by pathogens such as Fusarium, rust fungi and Septoria, can result in considerable losses in yield and quality.

The targeted use of fungicides plays a central role in disease control. Regular field inspections and consideration of weather conditions help with early detection and effective control.

Fungicide treatment only makes economic sense once the damage threshold has been exceeded. These control thresholds vary depending on the pathogen. Whether a damage threshold is exceeded often depends on site-specific factors, regional infestation pressure and weather conditions.

Wheat (Source: Own pictures)

Wheat (Source: Own pictures)

Imagine you are planning your fungicide treatment in wheat. Furthermore, imagine that you want to proceed according to the damage threshold principle in the situation described. In order to decide whether treatment is necessary and economically viable, you can seek advice to help you reduce yield losses.

For the optimal fungicide recommendation (time of application, dose, active ingredient), you can use a human advisor or an AI-based decision aid.

Both use the same data (e.g. field and farm-specific information, regional infection pressure, weather forecasts and available photos of the field) and deliver the recommendation by email within 24 hours.

The human advisor evaluates the data based on their experience, while the AI is based on an algorithm that has been trained with historical data. This means that past fungicide recommendations and their results are included in the analysis.

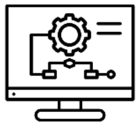
Please consider how much you would be willing to pay for the respective advisory service. We would like to take this opportunity to point out once again that this is a purely scientific survey and your information will not be used to determine a price for the advisory services.

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.

[Randomized from now on: Each participant must state their WTP three times for two different counseling options. The performance of the respective options varies so that either human advisor = AI-DST, human advisor > AI-DST or human advisor < AI-DST, in % [85,90,95], making 3x3=9 options from which three are randomly selected, ensuring that each of the three options is displayed once for the human advisor, in random order (draw without putting back), randomized for the AI-DST (version 1: draw with putting back, version 2: draw without putting back)].

You now have the choice between the following advisory services:

	Human advisor	**AI-based Decision Support Tool**
		
Correct past recommendation	***[85,90,95] %***	***[85,90,95] %***
How much would you be prepared to pay for a recommendation in €/ha? Please move the slider to the appropriate value. The amount applies per hectare for which you would like a recommendation.	0 € 150 €	0 € 150 €

Part 3: Ranking

Please rank the following advice options so that the best option for you is at the top and your least favorite option is at the bottom.

A. Advice on crop rotation planning from human advisor
B. Advice on fungicide strategies in wheat from human advisor
C. Advice on crop rotation planning by AI decision aid
D. Advice on fungicide strategies in wheat by AI decision aid
E. Advice on crop rotation planning from human advisor who analyzes results from AI decision aid and includes them in the advice
F. Advice on fungicide strategies in wheat from human advisor who analyzes result from AI decision aid and includes it in the advice

[same for everyone from now on]

Part 4: Questions on personal and operational characteristics

Technological engagement

To what extent do you agree with the following statements. You can use the scale to grade your statement from 1 “Do not agree at all” to 7 “Completely agree”.

- I am always interested in using the latest technology. *[TE 1 “Technological Interest”]*
- I find it difficult to deal with new technology - as a rule, I simply don’t know how to do it. *[TE 2 “Technological Competence Belief”, reverse coding]*
- When I deal with new technological developments, I have control over everything that happens. *[TE 3”Technological Control belief”]*

Which of the following digital technologies do you use? *[multiple choice]*

- o Apps for agriculture, namely: ___
- o Digital bookkeeping
- o Digital fertilizer planning
- o Digital field index
- o GPS steering systems
- o Smartphone
- o Section Control
- o Machine-controlled site-specific fertilization
- o Other, namely: ___

Experience

How would you rate your previous experience (in the last 5 years) with human farm advice?

- o Excellent
- o Very good
- o Good
- o Neither
- o Poor
- o Very bad
- o Insufficient
- o I have not made use of any human advice

How would you rate your previous experience (in the last 5 years) with digital decision aids (e.g.: field index, herd management, pest app)?

- ○ Excellent
- ○ Very good
- ○ Good
- ○ Neither
- ○ Poor
- ○ Very bad
- ○ Insufficient
- ○ I have not used any digital decision aids

Climate change

How would you rate the impact on your business in the following areas?

	Not concerned	Slightly concerned	Concerned	Very Concerned
More heavy rainfall events				
Longer periods of heat				
Reduced annual precipitation				
More extreme weather events (hail, storms, etc.)				
Increased soil erosion				
Increased flooding				
Increased waterlogging				
Increased pest pressure				

Risk attitude

How would you rate yourself personally?

Are you generally a risk-taking person or do you try to avoid risks?

You can use the scale to grade your statement from 0 “Not at all willing to take risks” to 10 “Very willing to take risks”. You can use the values in between to grade your assessment. 0 - Not at all willing to take risks

- ○ 0 - Not at all willing to take risks
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8
- ○ 9
- ○ 10 - Very willing to take risks

Age

How old are you? *[Dropdown with numbers from 18 to 99, incl. “no answer”]*

Farm size

How large is your farm (in ha)?

The farm size refers to the total agricultural area (owned and leased)).

- ○ under 5
- ○ 5-9
- ○ 10-19
- ○ 20-49
- ○ 50-99
- ○ 100 -199
- ○ 200 - 499
- ○ 500 -999
- ○ 1000 and more
- ○ not specified

Type of production

How do you manage your farm?

By “organic” we mean all farms that farm according to EU organic regulations or within the framework of farming associations (Bioland, Naturland, Demeter).

- o Conventional
- o Entire farm organic
- o Organic arable farming
- o Other areas organic
- o not specified

Questions and comments

Thank you for taking part in the survey!

Do you have any questions or comments? There’s space for them here:

______________________________________ *[free text]*

Lottery & Results

Would you like to take part in the competition?

o Yes → Forwarding to the competition

o No → Screen out

Would you like to receive the results of the survey?

Then enter your e-mail address on the following page. This will be stored separately from your answers in the survey so that the survey remains anonymous.

3.6.2 *B. Trace Plots*

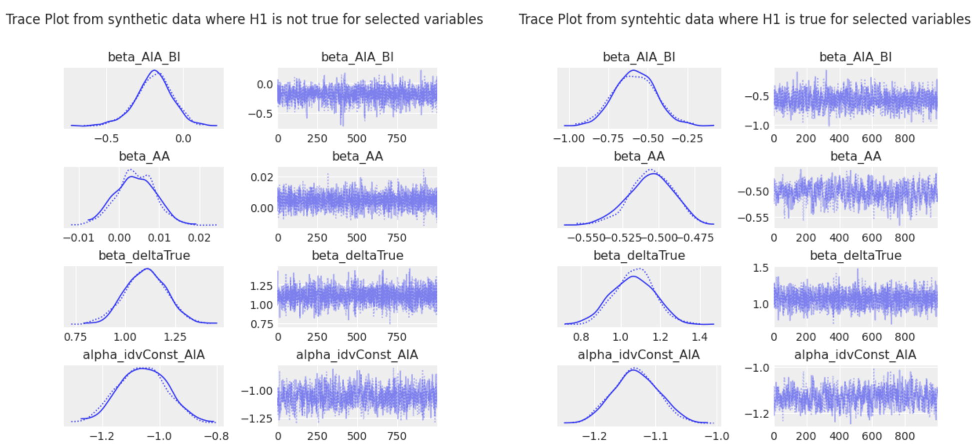


Figure 3.10: Trace plots for selected variables where Algorithm does not exist (left) and exists (right)

3.6.3 *C. Summary of the MCMC*

Table 3.4: Summary table for the MCMC

	mean	std	median	5.0%	95.0%	n_eff	r_hat
alpha_idvConst_AIA	1.05	0.08	1.05	0.92	1.17	1434.68	1.00
beta_AA	-0.35	0.03	-0.35	-0.40	-0.31	1378.02	1.00
beta_AIA_BI	-0.56	0.31	-0.54	-1.03	0.00	457.09	1.00
beta_AIA_EE	1.03	0.28	1.04	0.57	1.48	1947.33	1.00
beta_AIA_PE	0.67	0.25	0.67	0.28	1.09	1512.73	1.00
beta_AdvisorExperience_AIA	0.18	0.02	0.18	0.15	0.21	2339.68	1.00
beta_AdvisorExperience_EE	-0.48	0.09	-0.48	-0.63	-0.34	1859.15	1.00
beta_AdvisorExperience_PE	-0.36	0.08	-0.36	-0.48	-0.24	1917.69	1.00
beta_AdvisorExperience_SI	-0.10	0.09	-0.09	-0.26	0.04	410.10	1.00
beta_Age_AIA	0.00	0.02	0.00	-0.02	0.03	5199.85	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
beta_Age_EE	-0.22	0.08	-0.22	-0.34	-0.09	1743.74	1.00
beta_Age_PE	-0.05	0.07	-0.05	-0.15	0.06	2030.23	1.00
beta_Age_SI	-0.06	0.11	-0.03	-0.25	0.10	276.59	1.00
beta_DSTExperience_AIA	-0.09	0.02	-0.09	-0.12	-0.06	3829.49	1.00
beta_DSTExperience_EE	0.41	0.08	0.40	0.27	0.53	3405.99	1.00
beta_DSTExperience_PE	0.18	0.07	0.19	0.07	0.29	2917.10	1.00
beta_DSTExperience_SI	0.15	0.08	0.15	0.02	0.27	1147.18	1.00
beta_EE_BI	0.26	0.40	0.19	-0.34	0.96	348.75	1.00
beta_Farmsize_AIA	-0.14	0.02	-0.14	-0.17	-0.10	2377.46	1.00
beta_Farmsize_EE	0.15	0.08	0.15	0.01	0.29	1435.33	1.00
beta_Farmsize_PE	0.09	0.07	0.09	-0.01	0.22	2295.89	1.00
beta_Farmsize_SI	0.14	0.10	0.15	-0.04	0.28	330.76	1.00
beta_PE_BI	0.36	0.48	0.38	-0.44	1.12	1141.14	1.00
beta_RiskPref_AIA	-0.08	0.02	-0.08	-0.11	-0.05	4246.51	1.00
beta_RiskPref_EE	0.13	0.08	0.13	0.00	0.26	2407.49	1.00
beta_RiskPref_PE	0.14	0.07	0.14	0.03	0.24	2984.72	1.00
beta_RiskPref_SI	0.05	0.08	0.06	-0.09	0.19	576.38	1.00
beta_SI_BI	0.58	0.71	0.80	-0.73	1.51	208.81	1.00
beta_TechEngagement_AIA	-0.07	0.02	-0.07	-0.10	-0.03	2476.05	1.00
beta_TechEngagement_EE	0.68	0.08	0.68	0.54	0.82	3581.95	1.00
beta_TechEngagement_PE	0.46	0.07	0.46	0.36	0.57	3008.50	1.00
beta_TechEngagement_SI	0.23	0.08	0.23	0.08	0.35	2405.52	1.00
beta_deltaTrue	1.91	0.13	1.90	1.71	2.14	6314.59	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_AIA_1[0]	-0.10	0.21	-0.10	-0.45	0.25	4197.70	1.00
cutpoints_AIA_1[1]	1.05	0.20	1.05	0.74	1.39	3718.37	1.00
cutpoints_AIA_1[2]	1.78	0.18	1.78	1.47	2.06	3242.49	1.00
cutpoints_AIA_1[3]	2.77	0.15	2.77	2.54	3.03	2314.02	1.00
cutpoints_AIA_1[4]	4.03	0.15	4.03	3.78	4.26	2114.71	1.00
cutpoints_AIA_1[5]	5.36	0.19	5.36	5.04	5.66	2817.79	1.00
cutpoints_AIA_10[0]	-0.02	0.21	-0.02	-0.35	0.31	3957.75	1.00
cutpoints_AIA_10[1]	0.91	0.19	0.92	0.62	1.25	4305.76	1.00
cutpoints_AIA_10[2]	1.97	0.16	1.97	1.70	2.22	3353.34	1.00
cutpoints_AIA_10[3]	2.94	0.14	2.95	2.69	3.17	2591.47	1.00
cutpoints_AIA_10[4]	4.00	0.14	4.00	3.76	4.24	2208.37	1.00
cutpoints_AIA_10[5]	5.17	0.18	5.17	4.89	5.45	2943.71	1.00
cutpoints_AIA_11[0]	0.28	0.21	0.28	-0.05	0.65	3475.47	1.00
cutpoints_AIA_11[1]	1.63	0.18	1.63	1.33	1.92	3570.03	1.00
cutpoints_AIA_11[2]	2.43	0.16	2.43	2.16	2.69	2761.55	1.00
cutpoints_AIA_11[3]	3.34	0.15	3.34	3.10	3.58	2161.06	1.00
cutpoints_AIA_11[4]	4.49	0.16	4.50	4.22	4.74	1964.65	1.00
cutpoints_AIA_11[5]	5.68	0.21	5.68	5.33	6.01	2723.51	1.00
cutpoints_AIA_12[0]	0.42	0.20	0.41	0.08	0.75	3572.94	1.00
cutpoints_AIA_12[1]	1.85	0.17	1.85	1.55	2.10	2845.88	1.00
cutpoints_AIA_12[2]	2.79	0.15	2.79	2.55	3.04	2112.38	1.00
cutpoints_AIA_12[3]	4.18	0.16	4.18	3.92	4.44	1913.46	1.00
cutpoints_AIA_12[4]	5.23	0.19	5.23	4.93	5.56	2242.33	1.00
cutpoints_AIA_12[5]	6.50	0.28	6.50	6.01	6.92	3267.70	1.00
cutpoints_AIA_13[0]	0.84	0.20	0.84	0.53	1.15	3025.39	1.00
cutpoints_AIA_13[1]	2.29	0.16	2.29	2.03	2.55	2211.03	1.00
cutpoints_AIA_13[2]	3.11	0.15	3.11	2.86	3.35	1798.37	1.00
cutpoints_AIA_13[3]	4.44	0.17	4.44	4.15	4.69	2029.04	1.00
cutpoints_AIA_13[4]	5.49	0.20	5.48	5.14	5.80	2289.74	1.00
cutpoints_AIA_13[5]	6.84	0.31	6.83	6.32	7.33	3330.80	1.00
cutpoints_AIA_14[0]	0.80	0.19	0.80	0.48	1.10	3175.57	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_AIA_14[1]	2.19	0.16	2.19	1.93	2.46	2404.71	1.00
cutpoints_AIA_14[2]	3.16	0.15	3.15	2.90	3.38	1782.92	1.00
cutpoints_AIA_14[3]	4.56	0.16	4.56	4.28	4.82	1766.79	1.00
cutpoints_AIA_14[4]	5.60	0.21	5.60	5.26	5.95	2519.95	1.00
cutpoints_AIA_14[5]	6.88	0.32	6.87	6.40	7.39	3435.48	1.00
cutpoints_AIA_15[0]	1.10	0.18	1.11	0.81	1.40	2810.62	1.00
cutpoints_AIA_15[1]	2.68	0.15	2.67	2.43	2.91	2100.05	1.00
cutpoints_AIA_15[2]	3.63	0.15	3.63	3.39	3.87	1697.02	1.00
cutpoints_AIA_15[3]	5.00	0.18	5.00	4.69	5.27	1822.44	1.00
cutpoints_AIA_15[4]	6.16	0.24	6.15	5.79	6.59	2164.38	1.00
cutpoints_AIA_15[5]	7.34	0.38	7.33	6.73	7.94	2706.00	1.00
cutpoints_AIA_16[0]	0.89	0.19	0.91	0.56	1.19	3201.35	1.00
cutpoints_AIA_16[1]	2.51	0.15	2.51	2.29	2.79	2584.48	1.00
cutpoints_AIA_16[2]	3.41	0.15	3.41	3.17	3.67	2195.90	1.00
cutpoints_AIA_16[3]	4.77	0.17	4.77	4.50	5.05	2341.43	1.00
cutpoints_AIA_16[4]	5.98	0.24	5.97	5.59	6.37	3704.59	1.00
cutpoints_AIA_16[5]	6.93	0.32	6.92	6.42	7.46	3484.29	1.00
cutpoints_AIA_2[0]	-0.22	0.22	-0.21	-0.55	0.16	4187.35	1.00
cutpoints_AIA_2[1]	0.74	0.20	0.74	0.45	1.09	3410.58	1.00
cutpoints_AIA_2[2]	1.56	0.18	1.56	1.25	1.84	2850.39	1.00
cutpoints_AIA_2[3]	2.57	0.15	2.57	2.32	2.82	2202.19	1.00
cutpoints_AIA_2[4]	3.60	0.14	3.60	3.35	3.82	1873.71	1.00
cutpoints_AIA_2[5]	5.05	0.18	5.04	4.78	5.37	2245.59	1.00
cutpoints_AIA_3[0]	0.45	0.20	0.45	0.12	0.76	3620.28	1.00
cutpoints_AIA_3[1]	1.61	0.17	1.61	1.34	1.87	2980.82	1.00
cutpoints_AIA_3[2]	2.60	0.15	2.60	2.35	2.83	2057.14	1.00
cutpoints_AIA_3[3]	3.41	0.14	3.41	3.16	3.64	1900.16	1.00
cutpoints_AIA_3[4]	4.47	0.16	4.47	4.21	4.73	1916.76	1.00
cutpoints_AIA_3[5]	5.87	0.23	5.86	5.51	6.26	2940.33	1.00
cutpoints_AIA_4[0]	0.06	0.23	0.06	-0.30	0.45	3221.32	1.00
cutpoints_AIA_4[1]	1.02	0.20	1.02	0.71	1.37	3048.31	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_AIA_4[2]	2.24	0.16	2.24	2.00	2.51	2382.84	1.00
cutpoints_AIA_4[3]	3.06	0.14	3.06	2.83	3.30	2071.05	1.00
cutpoints_AIA_4[4]	4.27	0.15	4.27	4.00	4.51	2006.45	1.00
cutpoints_AIA_4[5]	5.48	0.19	5.48	5.19	5.82	2604.17	1.00
cutpoints_AIA_5[0]	0.05	0.21	0.06	-0.29	0.39	2856.32	1.00
cutpoints_AIA_5[1]	1.22	0.19	1.23	0.94	1.55	3560.45	1.00
cutpoints_AIA_5[2]	2.20	0.16	2.20	1.93	2.45	2380.55	1.00
cutpoints_AIA_5[3]	3.17	0.15	3.17	2.92	3.43	2052.54	1.00
cutpoints_AIA_5[4]	4.06	0.16	4.05	3.81	4.32	2071.59	1.00
cutpoints_AIA_5[5]	5.30	0.19	5.30	4.99	5.61	2534.60	1.00
cutpoints_AIA_6[0]	0.49	0.21	0.50	0.17	0.84	2964.71	1.00
cutpoints_AIA_6[1]	1.88	0.17	1.88	1.62	2.18	3375.44	1.00
cutpoints_AIA_6[2]	2.74	0.15	2.74	2.47	2.98	2443.74	1.00
cutpoints_AIA_6[3]	4.07	0.15	4.07	3.81	4.31	2001.45	1.00
cutpoints_AIA_6[4]	4.87	0.17	4.87	4.60	5.14	2277.12	1.00
cutpoints_AIA_6[5]	5.93	0.23	5.91	5.60	6.33	2811.25	1.00
cutpoints_AIA_7[0]	0.64	0.20	0.64	0.31	0.95	3110.41	1.00
cutpoints_AIA_7[1]	1.91	0.17	1.91	1.65	2.19	2141.65	1.00
cutpoints_AIA_7[2]	2.78	0.15	2.78	2.54	3.04	1949.00	1.00
cutpoints_AIA_7[3]	3.60	0.15	3.60	3.37	3.85	1797.57	1.00
cutpoints_AIA_7[4]	4.90	0.18	4.89	4.62	5.20	1944.09	1.00
cutpoints_AIA_7[5]	5.93	0.23	5.92	5.53	6.29	2962.07	1.00
cutpoints_AIA_8[0]	-0.47	0.22	-0.46	-0.84	-0.13	4205.79	1.00
cutpoints_AIA_8[1]	0.25	0.21	0.26	-0.09	0.61	4545.21	1.00
cutpoints_AIA_8[2]	0.84	0.20	0.85	0.51	1.15	4001.68	1.00
cutpoints_AIA_8[3]	1.73	0.18	1.73	1.43	2.00	3673.16	1.00
cutpoints_AIA_8[4]	3.16	0.14	3.16	2.93	3.39	2008.14	1.00
cutpoints_AIA_8[5]	4.39	0.15	4.39	4.16	4.65	2199.03	1.00
cutpoints_AIA_9[0]	-0.15	0.23	-0.16	-0.53	0.22	3705.05	1.00
cutpoints_AIA_9[1]	0.73	0.22	0.74	0.38	1.09	3882.62	1.00
cutpoints_AIA_9[2]	1.69	0.18	1.70	1.40	1.99	3187.72	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_AIA_9[3]	2.97	0.15	2.97	2.74	3.21	2221.63	1.00
cutpoints_AIA_9[4]	4.13	0.15	4.13	3.89	4.38	2182.35	1.00
cutpoints_AIA_9[5]	5.81	0.22	5.80	5.45	6.16	3100.86	1.00
cutpoints_BI_1[0]	0.40	0.30	0.40	-0.12	0.87	2834.33	1.00
cutpoints_BI_1[1]	1.47	0.29	1.47	1.00	1.95	2673.92	1.00
cutpoints_BI_1[2]	2.34	0.29	2.34	1.91	2.86	2565.89	1.00
cutpoints_BI_1[3]	3.73	0.32	3.73	3.21	4.24	2693.75	1.00
cutpoints_BI_1[4]	5.17	0.37	5.16	4.57	5.77	3034.55	1.00
cutpoints_BI_1[5]	6.21	0.45	6.19	5.48	6.93	3423.52	1.00
cutpoints_BI_2[0]	0.13	0.30	0.13	-0.35	0.62	2579.01	1.00
cutpoints_BI_2[1]	1.03	0.29	1.03	0.57	1.53	2396.98	1.00
cutpoints_BI_2[2]	2.06	0.29	2.05	1.59	2.53	2482.78	1.00
cutpoints_BI_2[3]	3.12	0.31	3.12	2.62	3.62	2611.09	1.00
cutpoints_BI_2[4]	4.64	0.34	4.63	4.07	5.18	2909.49	1.00
cutpoints_BI_2[5]	6.38	0.47	6.36	5.62	7.14	3629.65	1.00
cutpoints_BI_3[0]	-0.57	0.31	-0.56	-1.07	-0.06	2526.40	1.00
cutpoints_BI_3[1]	0.54	0.30	0.53	0.04	1.03	2552.93	1.00
cutpoints_BI_3[2]	1.11	0.30	1.10	0.63	1.59	2445.19	1.00
cutpoints_BI_3[3]	2.01	0.30	2.00	1.52	2.51	2260.96	1.00
cutpoints_BI_3[4]	3.51	0.31	3.50	2.99	4.00	2505.52	1.00
cutpoints_BI_3[5]	4.93	0.36	4.92	4.31	5.48	2912.26	1.00
cutpoints_EE_1[0]	-0.37	0.34	-0.37	-0.91	0.21	2965.86	1.00
cutpoints_EE_1[1]	0.49	0.33	0.48	-0.04	1.04	2279.89	1.00
cutpoints_EE_1[2]	1.89	0.32	1.89	1.33	2.40	2113.16	1.00
cutpoints_EE_1[3]	3.02	0.32	3.02	2.49	3.53	1921.13	1.00
cutpoints_EE_1[4]	4.34	0.32	4.34	3.80	4.84	1871.56	1.00
cutpoints_EE_1[5]	6.17	0.38	6.16	5.54	6.80	2344.30	1.00
cutpoints_EE_2[0]	-0.50	0.36	-0.50	-1.15	0.04	3099.77	1.00
cutpoints_EE_2[1]	0.45	0.35	0.46	-0.12	1.02	2563.76	1.00
cutpoints_EE_2[2]	1.62	0.33	1.63	1.10	2.16	2180.34	1.00
cutpoints_EE_2[3]	2.60	0.32	2.61	2.06	3.12	2062.71	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_EE_2[4]	4.07	0.31	4.07	3.59	4.62	1991.87	1.00
cutpoints_EE_2[5]	6.30	0.38	6.29	5.71	6.96	2378.25	1.00
cutpoints_EE_3[0]	-0.32	0.35	-0.32	-0.91	0.21	2632.65	1.00
cutpoints_EE_3[1]	1.07	0.32	1.08	0.54	1.60	2137.41	1.00
cutpoints_EE_3[2]	1.92	0.32	1.92	1.40	2.46	2050.89	1.00
cutpoints_EE_3[3]	2.85	0.32	2.85	2.33	3.39	2085.23	1.00
cutpoints_EE_3[4]	4.34	0.32	4.34	3.77	4.84	2030.20	1.00
cutpoints_EE_3[5]	6.32	0.38	6.31	5.65	6.90	2321.03	1.00
cutpoints_PE_1[0]	-0.20	0.33	-0.19	-0.77	0.32	2760.10	1.00
cutpoints_PE_1[1]	0.99	0.30	1.00	0.46	1.45	2008.26	1.00
cutpoints_PE_1[2]	1.82	0.29	1.82	1.27	2.24	1857.30	1.00
cutpoints_PE_1[3]	2.57	0.29	2.57	2.11	3.06	1709.08	1.00
cutpoints_PE_1[4]	3.66	0.29	3.66	3.16	4.10	1674.79	1.00
cutpoints_PE_1[5]	5.49	0.34	5.49	4.94	6.07	2201.94	1.00
cutpoints_PE_2[0]	-0.02	0.31	-0.03	-0.54	0.48	2363.03	1.00
cutpoints_PE_2[1]	0.94	0.29	0.94	0.46	1.40	1902.79	1.00
cutpoints_PE_2[2]	1.80	0.28	1.80	1.34	2.25	1660.00	1.00
cutpoints_PE_2[3]	2.82	0.28	2.82	2.37	3.29	1711.94	1.00
cutpoints_PE_2[4]	4.22	0.29	4.21	3.74	4.69	1623.56	1.00
cutpoints_PE_2[5]	5.93	0.35	5.93	5.32	6.49	1963.26	1.00
cutpoints_PE_3[0]	-0.29	0.35	-0.29	-0.82	0.32	2173.34	1.00
cutpoints_PE_3[1]	0.65	0.31	0.64	0.15	1.18	2037.05	1.00
cutpoints_PE_3[2]	1.95	0.30	1.96	1.50	2.48	1606.86	1.00
cutpoints_PE_3[3]	3.33	0.29	3.33	2.88	3.82	1553.95	1.00
cutpoints_PE_3[4]	4.47	0.30	4.47	3.98	4.94	1630.72	1.00
cutpoints_PE_3[5]	6.09	0.37	6.07	5.49	6.66	2070.15	1.00
cutpoints_PE_4[0]	-0.27	0.33	-0.26	-0.80	0.28	2290.19	1.00
cutpoints_PE_4[1]	0.76	0.31	0.77	0.27	1.27	2131.91	1.00
cutpoints_PE_4[2]	1.74	0.29	1.73	1.25	2.19	1705.74	1.00
cutpoints_PE_4[3]	2.87	0.28	2.87	2.41	3.32	1580.47	1.00
cutpoints_PE_4[4]	4.08	0.29	4.08	3.59	4.55	1628.99	1.00

	mean	std	median	5.0%	95.0%	n_eff	r_hat
cutpoints_PE_4[5]	5.91	0.36	5.91	5.27	6.46	2128.63	1.00
cutpoints_SI_1[0]	0.14	0.20	0.15	-0.18	0.46	3094.81	1.00
cutpoints_SI_1[1]	1.05	0.16	1.06	0.78	1.30	3731.31	1.00
cutpoints_SI_1[2]	1.89	0.13	1.89	1.67	2.09	2559.03	1.00
cutpoints_SI_1[3]	4.40	0.18	4.40	4.09	4.67	2991.33	1.00
cutpoints_SI_1[4]	5.63	0.29	5.61	5.15	6.10	3981.21	1.00
cutpoints_SI_1[5]	7.02	0.52	6.98	6.16	7.84	4379.46	1.00
cutpoints_SI_2[0]	-0.09	0.22	-0.08	-0.44	0.25	3705.02	1.00
cutpoints_SI_2[1]	0.77	0.19	0.78	0.48	1.08	3402.49	1.00
cutpoints_SI_2[2]	1.69	0.14	1.69	1.44	1.90	2669.56	1.00
cutpoints_SI_2[3]	3.83	0.16	3.82	3.58	4.09	2333.33	1.00
cutpoints_SI_2[4]	5.06	0.23	5.06	4.68	5.44	3503.27	1.00
cutpoints_SI_2[5]	6.49	0.40	6.47	5.85	7.16	3278.42	1.00

3.6.4 *D. Prior and Posterior Coefficient plots*

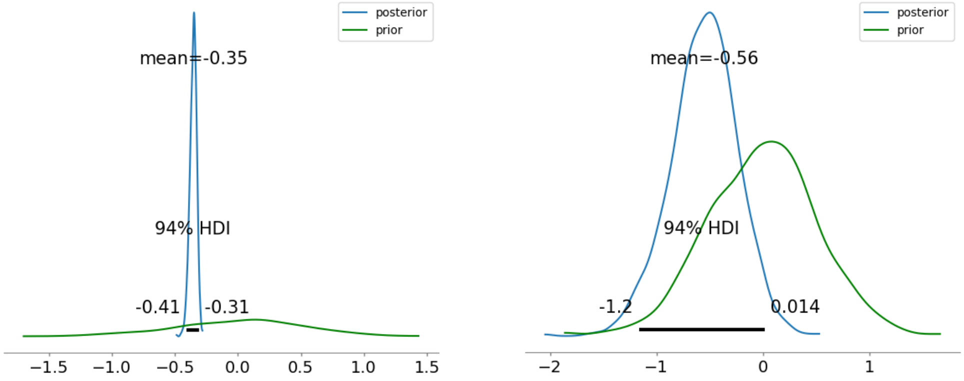


Figure 3.11: Prior and posterior distribution of coefficients of interest. Black bar indicating HPDI.

Figure 3.11 shows the prior and posterior distribution of our two coefficients of interest, β_{AA} (right) and $\gamma_{AIA}(left)$. As it can be seen, the model updated the distributional assumptions based on the survey data.

Chapter 4

Action- or results-based payments for ecosystem services in the era of smart weeding robots?*

Abstract. Payments for ecosystem services (PES) are commonly used to reduce negative impacts on biodiversity by intensive agricultural production. Whether action- or results-based, the efficiency of PES schemes in terms of conservation benefit per costs, hinges on cost-effective monitoring, actions farmers are rewarded for, appropriate biodiversity indicators and, farmers' acceptance. Despite expectations that novel technologies, such as weeding robots, will reduce monitoring costs, the potential impact of their widespread use on optimal PES design for biodiversity conservation in arable farming remains unexplored. Our study investigates 1) the influence of weeding robots on optimal scheme design and 2) the challenges and options that arise for future PES scheme design. To this end, we use a simulation model to systematically compare how the availability of weeding robots changes the preferability of action-based versus results-based payments under various production and management conditions. This study sheds light on the transformative potential of weeding robots in optimizing PES for biodiversity conservation. The results indicate that the difference in efficiency between action- and results-based schemes vanishes if robots can perform biodiversity-sensitive actions. Further, we find that it is even more important for the future design of PES to be able to define multidimensional biodiversity goals - a major challenge calling for interdisciplinary research.

Keywords: *Payments for Ecosystem Services, Weeding Robot, Payment by Result, Biodiversity Conservation, Crop Production*

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4.1 Introduction

Payments for ecosystem services (PES) are a widely used tool to reduce the negative impacts of agricultural production on biodiversity (Wunder et al., 2008). PES for biodiversity conservation can be organized as either action-based schemes (ABS), in which farmers are rewarded for executing a certain action, or as results-based schemes (RBS), in which farmers receive money in return for the provision of predefined biodiversity indicators. The efficiency of such PES schemes, defined as the conservation benefits per cost of the agency (Ansell et al., 2016), hinges on several factors. Cost-effective monitoring, defined as the value of the indicator vs. effort to monitor it (Lindenmayer et al., 2012)), is only one of several factors determining the efficiency of a PES scheme. Also, the actions that farmers are rewarded for, appropriate biodiversity indicators, and, farmers' acceptance are crucial to the efficiency of such schemes. Research suggests that digitalization will change how agricultural policy instruments are designed (Ehlers et al., 2021) and that the monitoring abilities of novel technologies, e.g. through acoustic monitoring or digital fencing (Biffi et al., 2024; Wätzold et al., 2024) will induce a shift towards results-based schemes (Besson et al., 2022; Finger, 2023). However, these assumptions are largely conceptual and have not been fully investigated. Moreover, other characteristics of technologies might induce changes, even in unintended directions. However, these consequences remain to be sufficiently studied (Basso and Antle, 2020).

Therefore, in this study, we explore how optimal PES design for biodiversity conservation changes if smart weeding robots are available for crop production. With smart weeding robots we mean novel autonomous selective weeding robots[†] (hereafter, weeding robots). Weeding robots have the potential to decrease negative impacts on biodiversity while allowing for high yields by selectively removing weeds with non-chemical tools or

[†] As the term 'robot' has not been clearly defined (Merfield, 2016; Moreno et al., 2024), here, we define a weeding robot as 'a mobile, autonomous, decision making, mechatronic device that accomplishes weeding under human supervision, but without direct human labor, adopting the definition of Lowenberg-DeBoer et al. (2020).

variable-rate application of herbicides (Bawden et al., 2017; Fennimore & Cutulle, 2019; Slaughter et al., 2008; Storm, Seidel, et al., 2024; Zhang et al., 2022). We aim to achieve our objective by answering the following research questions:

1) How do weeding robots affect optimal PES scheme designs?

2) What challenges and options might arise for future scheme designs once weeding robots are used?

Previous studies of optimal PES designs range from theoretical works focusing on information asymmetry between landowners and conservation buyers, risk and payment mechanisms (Derissen & Quaas, 2013; Ferraro, 2008; McDonald et al., 2018; White & Hanley, 2016; Zabel & Roe, 2009) to reviews of PES effectiveness in different contexts (Börner et al., 2017; Wunder et al., 2008) to empirical studies investigating farmers' stated and revealed preferences for various PES designs (Canessa et al., 2023; Massfeller et al., 2022; Rasch et al., 2021). Gibbons et al. (2011) developed a simulation model to investigate the conditions under which ABS and RBS are more efficient by considering the characteristics of the management, the targeted biodiversity, and the landscape.

Most schemes in developed countries pay farmers for actions, e.g., within the common agricultural policy (CAP) of the EU (European Commission, 2021b; Gibbons et al., 2011). However, an increased focus on RBS has been observed in recent years (BMEL, 2023; European Commission, 2023; Pe'er et al., 2022). One driver for this development is the critique of ABS as inefficient, as they do not deliver the anticipated results and are costly to the taxpayer (Batáry et al., 2015; Brown et al., 2021; Pe'er et al., 2020). RBS form one attempt to minimize such inefficiencies, as the payment is tied to the occurrence of predefined results. While in both cases, farmers facing low costs for joining the scheme are incentivized to participate and some might be overpaid, under RBS, as opposed to ABS, biodiversity service provision is ensured. By providing farmers with greater flexibility in determining the measures they implement to achieve the predefined objective, social and cultural capital is enhanced, which could promote acceptance (Burton & Schwarz, 2013). However, the financial risk that farmers face if the predefined targets are not reached despite efforts, and the need to define measurable indicators that can be monitored at low cost has impeded the broad-scale implementation of RBS (Burton & Schwarz, 2013; Zabel & Roe, 2009).

Evidence from Europe (Elmiger et al., 2023; Hagemann et al., 2025), the US (Baylis et al., 2008) and Australia (Connor et al., 2008) indicates that most implemented RBS primarily focus on biodiversity in grassland and extensification or wildlife conservation. In contrast, only a few European RBS target biodiversity conservation in arable farming (Hagemann et al., 2025). Examples include "RBPS for biodiversity on arable and upland grassland systems in England" in the UK (Chaplin et al., 2021), "Protecting farmland pollinators" in Ireland (RBPN, 2019) or "Proof of Ecological Performance (PEP) and Biodiversity payments" in Switzerland (RBPN, 2019). In Germany, only one scheme in arable farming is implemented, targeting harrier nests (LANUV, 2023), and one focusing on weed occurrence was hypothetically tested (Massfeller et al., 2022). However, engagement in biodiversity conservation is especially needed in intensive crop production areas (Scheper et al., 2023; Stein-Bachinger et al., 2022).

To fill the two research gaps of 1) the missing evidence for the effects of novel technology on PES efficiency and 2) the lack of efficient PES targeting biodiversity in intensive arable farming, we adopt Gibbons et al.'s (2011) simulation model and apply it on the case of a PES for biodiversity conservation in arable farming with weeding robots. We use this model to simulate how weed management conditions will likely change, considering not only improved monitoring capabilities but also the weeding robots' ability to selectively remove weeds and changes in cost structures. We first derive the PES design parameters that are likely to be influenced by weeding robots and model the effects on the optimal scheme design for the efficiency of both ABS and RBS scheme types. Based on the results of the simulation we discuss the arising challenges and options for future scheme design and identify research needs. Throughout the study, we assume a risk-neutral farmer. As risk is an important feature of PES (Bolton and Dewatripont, 2004) and European farmers have been found to be rather risk averse (Garcia et al., 2024), this is an important aspect we come back to in the discussion.

This study sheds light on the transformative potential of weeding robots for optimizing PES schemes for biodiversity conservation in arable farming. We focus on the provision of food and shelter for insects through weeds as targeted biodiversity service, measured through the occurrence of certain weeds (in a certain distribution or density). Contrarily to “traditional” weeding with tractor-mounted machinery where the action is defined at the field level (e.g. to weed mechanically or to spray herbicides), weeding robots will be able to remove weeds selectively based on different rationales like weed species, weed density, or the competitiveness between weeds and crops as tested by Zingsheim and Döring (2024). Due to this selective weeding ability, novel management actions can be defined such that the desired biodiversity reacts sensitively and in the desired direction. Our findings indicate that the difference in efficiency, i.e. biodiversity benefit over agency cost, between ABS and RBS vanishes if robots can perform biodiversity-sensitive actions. We define biodiversity-sensitive actions through the robot’s ability to selectively remove weeds at the individual plant level.

Hence, while robots’ monitoring capability could reduce monitoring costs and thereby benefit RBS’ efficiency, we find that the execution of sensitive actions through selective weeding might be an even more important feature of weeding robots for the relative efficiency of PES. Additionally, based on our results we discuss that it is more important for future PES designs to define multidimensional biodiversity goals. Our findings have implications for future policy design and the development of novel technologies and indicate interdisciplinary research needs. Future empirical studies on optimal PES design using weeding robots may draw on our insights.

We proceed by taking an interdisciplinary perspective on how weeding robots change weed management, incorporating expertise from ecology research and technology development (Section 2). Section 2 serves to provide the background information on which we build our modelling assumptions and discussion in the following sections. In Section 3, we present the model and explain our application to weeding robot use. After analyzing the simulation results in Section 3, we discuss policy recommendations, options and challenges for future PES design in Section

4. We conclude in Section 5 by providing implications for future interdisciplinary research.

4.2 Changes in weed management when weeding robots are available

Because crops and weeds compete for resources (Guglielmini et al., 2017; Oerke, 2006; Thompson et al., 2019; Zimdahl, 2007), farmers typically face a trade-off between yield gain (i.e. the gain in yield compared to no weeding) and weed biodiversity when removing weeds (Campiglia et al., 2018). On the one hand, the use of herbicides at the field level tends to reduce weeds that serve as food and habitat for insects and other animals (Beckmann et al., 2019; Geiger et al., 2010; Hole et al., 2005; S. Meyer et al., 2013). On the other hand, weeds cause the highest yield losses of all pests (Oerke, 2006), endangering the production of food and feed for a growing world population (Savary et al., 2019; Schneider et al., 2023).

Currently, farmers are generally able to decide between conventional herbicide-based weed management (Bawden et al., 2017), mechanical weeding (Ahmadi et al., 2021; BMEL, 2023) and integrated weed management (IWM) approaches (Kunz, 2017). In the EU, farmers are legally required to consider the guidelines of IWM (European Commission, 2024). An intensive use of conventional herbicide-based weed management usually generates higher yields as more weeds are removed, but it typically leads to lower weed biodiversity (Campiglia et al., 2018; Gerhards et al., 2020; Kunz et al., 2018; Pannacci and Tei, 2014). With mechanical weeding, which is primarily used in organic farming or IWM, fewer weeds are usually removed, leading to higher weed biodiversity but lower yields (Batáry et al., 2017; Tscharntke et al., 2021). However, the weed-biodiversity-yield gain relationship is highly context-dependent (Colbach et al. 2020) and is largely governed by farming intensity (Berquer et al., 2023). Importantly, in each of the three approaches, the level of the remaining weeds is to a large part a random outcome, resulting primarily from the varying efficiency of each working step.

Weeding robots are currently used by EU farmers mainly in herbicide-intensive row crops, such as sugar beets (Duckett et al., 2018). Future weeding robots might allow purposeful decisions with respect to the level of weeds in the field, thereby reducing the trade-off between yield and biodiversity. We follow Merfield (2023) and categorise different levels of weeding robots: Weeding robots that remove every plant that is not a crop by 'remembering' where they had sown, and weeding robots that can differentiate between crop and non-crop plants (e.g. Walter et al. (2018)) are referred to as level 2 and 3, respectively. So-called 'level 4 weeding robots' have two essential abilities that differentiate them from previous levels: 1) *removing ability*: they can remove weeds efficiently and selectively using various techniques (laser, mechanical and chemical) (Ahmadi et al., 2022), drawing on different types of input information, such as the number of weed species, historical yield or soil properties (Zingsheim & Döring, 2024) and 2) *monitoring ability*: they can identify and monitor different plant and weed species. While most of the robots that are market-ready and currently in use are in level 2 or 3, within this study, we assume the availability of 'level 4 weeding robots', which are currently in the prototype stage (Ahmadi et al., 2022; Li et al., 2019).

The main challenge for implementing biodiversity-aware weeding with vision-based systems is the accurate distinction between crops and beneficial and harmful weeds, under various conditions. This sophistication must be complemented by specially designed, robust hardware. It needs to ensure that the system can make quick and accurate decisions and execute precise actions, such as targeted weeding, without damaging the crops or the soil. Such a system also needs to be economical and user-friendly, as these are key factors for adoption by farmers (Rose et al., 2018). Against this background, we identify three major changes in weed management when "level 4 robots" are used instead of 'traditional' weeding done by tractor-mounted machinery.

First, "level 4 robots" will be able to selectively remove weeds based on species, density, distribution, or other criteria. Thereby they will enable accounting for naturally non-uniform weed distributions across the field (Borgy et al., 2012) and for varying competitiveness across weed species

(Marshall et al., 2003). Because weeds can be detected and removed selectively and in a site-specific way where they occur, similar to the threshold procedure in IWM (Young, 2018), the level of biodiversity in the field can be deliberately set. This can reduce the trade-off between yield and biodiversity as shown by Zingsheim and Döring (2024). They tested different weeding strategies that robots could execute based on different rationales such as weed density, competitiveness between weed and crop or by strip-wise weed removal. They found that biodiversity in terms of alpha- or gamma-diversity increases by up to 80% while maintaining yield effects. For example, if only very crop-damaging weeds are removed while others can remain, high yield can still be obtained, while also more biodiversity can remain on the field. Thereby, the probability increases that the desired biodiversity service, for example in terms of weeds serving as food and shelter for insects, occurs on the plot.

Second, the robots' monitoring ability will allow to identify and monitor crops and weeds more reliably compared to humans (Ahmadi et al., 2021; Bawden et al., 2017; Pandey et al., 2021; Wu et al., 2020; Zhang et al., 2022). A common performance metric to evaluate object detection of autonomous devices is the mean average precision (mAP) which is close to 90% in recently developed detection algorithms and steadily increasing (Weyler et al., 2024). Given this improved detection performance, not only biodiversity and crops but also (non-)compliance with a certain action (in the ABS case) could be detected, e.g. robots could detect whether chemical plant protection was used or if a certain seed row distance was maintained (Ahmadi et al., 2021; BMEL, 2023). If the conservation buyer ("the agency") has access to the data collected from participants in the scheme, and if we assume that this data remains untampered by the farmers, we can conclude that: 1) the detectability of biodiversity indicators as well as of non-compliance with the scheme will increase and 2) agency employees will no longer need to visit the farm to monitor compliance or biodiversity service occurrence, thereby decreasing the costs for the agency.

As a third effect, the availability of weeding robots could alter the distribution of costs associated with weeding. This might be due to changes in investment costs, labor and supervision time, efficiency, and resource usage but it is very complex, especially when taking weed-yield dynamics into account (Lowenberg-DeBoer, 2019; Lowenberg-DeBoer, Franklin, et al., 2021; Shang et al., 2023; Yu et al., 2024).

4.3 Material and Methods

Text In this study, we use and extend the theoretical model provided by Gibbons et al. (2011) to evaluate the ways in which the availability of weeding robots affects preference for RBS or ABS. The model is useful for answering our research questions considering the influence of the properties of weed management on the provision of biodiversity and scheme efficiency. Considering how weeding robots may impact changes in weed management, we can elicit how the availability of level-4 robots might change the relative preferability of ABS and RBS. The process-based model we consider is based on Gibbons et al.'s work (2011) and derived from theory and expert knowledge. Thereby it allows to study novel, not yet existing, technologies and policy schemes that cannot yet be examined empirically: to date, only a few weeding robots are actually adopted by farmers, and there are only a few implemented results-based schemes in arable farming. Hence, data on this topic are scarce.

To describe our model, we follow the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm et al., 2006), as updated by Grimm et al. (2020 a; 2020 b). We provide the ODD summary in Section 3.1. For a detailed overview of the model, including all relevant equations, all parameters and how we extended the original model by Gibbons et al. (2011), see the full ODD protocol and especially Table 2 in the supplementary material.

Based on the diagnosed changes in weed management arising through the availability of weeding robots in Section 2, in the following, we first present the overall set-up of the model and second identify the relevant parameters in the model to reflect the identified changes from Section 2. As a third step, we define plausible directions and ranges of how each parameter might be affected by weeding robots and, fourth, use those ranges to simulate and compare the relative preferability of RBS and ABS when weeding robots are available. In Table 4.1 we present the outcome of steps 1–3. As there are only a few results-based schemes in arable farming (yet), the availability of empirical information is very limited. However, whenever possible we base our assumptions for step 3) on empirical evidence.

4.3.1 *The model*

The simulation model initially developed by Gibbons et al. (2011) is designed to evaluate Payments for Ecosystem Services (PES) aimed at biodiversity conservation. The overall purpose of the model is to illustrate how the properties of the targeted biodiversity service, of the management action, and the initial distribution of the biodiversity service in the landscape influence the provision of the targeted biodiversity service. The model offers a comparative theoretical framework to contrast two PES types: action-based schemes (ABS), where farmers are paid for specific management actions, and results-based schemes (RBS), which reward observed biodiversity outcomes.

The purpose of our study is to evaluate the effect of robotic weeding availability on scheme efficiency (conservation benefit per agency cost). Therefore, we extend the model by considering additional properties such as the agency's monitoring costs, the farmers' costs of executing a certain management action, as well as properties of the technology. In contrast to the original model, we consider the plot level to avoid too strong assumptions on technology use on the landscape level. Concerning the temporal resolution, the model depicts one point in time (one production period) on one plot. It is set up in R programming language. Model initialization does not involve empirical data. The whole model construction relies on theoretical assumptions and expert knowledge.

To consider our model realistic enough for its purpose, we use patterns of biodiversity service provision and scheme efficiency (see Figures 4.2, 4.3, and 4.4a-c in Section 4). The model includes five main entities: (1) the targeted biodiversity service, (2) management actions, (3) the plot, (4) human actors, specifically the farmer and the agency, and (5) the technology (weeding robot). The state variables characterizing these entities are provided in Table 1 in the ODD protocol.

The targeted biodiversity service represents the goal of the PES, constructed as a binary outcome indicating the presence or absence of a specific service. In the present study, we focus on the provision of food and habitat for insects through weeds as targeted biodiversity service. The biodiversity service is assumed to occur if a specific desired biodiversity can be found on the plot. This can be the presence of certain (indicator) weeds or reaching pre-defined thresholds of species abundance, density, and distribution.

Figure 4.1 provides an overview of the model processes. The main idea is, that the probability that the desired biodiversity and thereby the biodiversity service occurs increases through management actions defined within PES. Management actions can vary based on the PES type, with farmers either following prescribed actions (ABS) or choosing actions to optimize biodiversity outcomes (RBS). Each plot has an initial probability of biodiversity service occurrence before PES intervention, and each management action comes with a certain sensitivity describing how the desired biodiversity reacts to the action (for more details on this parameter, see Section 7.1. in the ODD protocol including a concrete example).

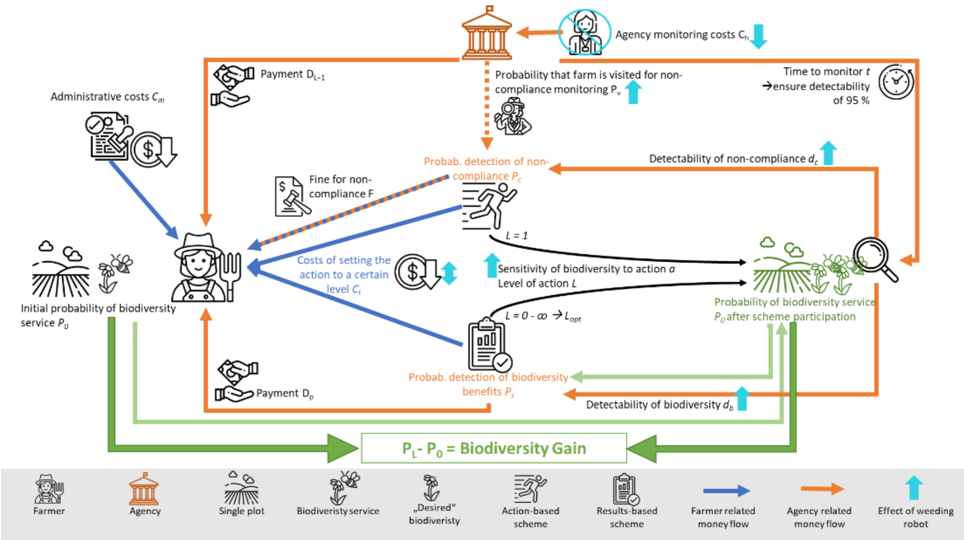

Figure 4.1: Simplified Model Process

In the model, the farmer seeks to maximize income through scheme participation, while the agency aims to achieve the highest biodiversity gain at the lowest cost. In ABS, the agency specifies actions and the farmer is compensated for executing them at the required level. The farmer could also voluntarily go beyond the minimum standards without receiving additional payment. Examples of existing plot-level ABS in Germany in arable farming that aim at biodiversity conservation are the prohibition of using chemical plant protection products or an increase in the seed distance (Landwirtschaftskammer, 2022).

In RBS, however, farmers have more flexibility in what actions to take, as payments are based on the achieved biodiversity outcome. For example, compared to the aforementioned ABS of no chemical application, farmers could decide to restrict chemical application to only certain areas within a plot (lower level) or could additionally adjust practices like seed distance to impact the biodiversity outcome positively (higher level).

Two key decision-making dynamics drive the model: 1) Farmers decide to join PES schemes based on whether they expect to gain income from it, factoring in management costs, payments, and potential penalties for non-compliance. The payment is defined as a multiple of the management costs.[‡] The agency, meanwhile, optimizes its budget by balancing expenses on payments and monitoring costs that strongly depend on how easily desired biodiversity and compliance can be detected.

The model's outputs—gain in probability of biodiversity occurrence ("biodiversity gain") and associated costs—provide insights into scheme efficiency. Scheme efficiency is quantified as the biodiversity gain per unit of agency expenditure, and used to compare ABS and RBS. Note that the model does not consider the complexity of ecological and agricultural processes of weed-yield dynamics, as this is not within the scope of our study, but was, for example, done by Yu et al. (2024).

[‡] For our analysis, we fix the payment at a certain level in order to reduce the dimensions considered in the analysis. We conduct a sensitivity analysis considering a range of values for the payment as described in the Appendix A.

4.3.2 *Linking changes in weed management to model parameters*

Based on the model description in Section 3.1 and the diagnosed impacts of weeding robots on the conditions of weed management in Section 2, we identified the model parameters that are relevant to reflecting these conditions. We summarize the parameters that we assume to be impacted by robots in Table 4.1. Additionally, the table summarizes the considered parameter ranges and the empirical basis for these ranges. In the following subsections, we go through each of the identified changes and discuss the derived parameter ranges in detail.

Removing ability

To reflect the robot's selective weed removal ability in the model, we turn to parameter a, the sensitivity of the biodiversity to the action. In the model, the parameter describes how the desired biodiversity reacts to the management action and is considered as a property of the management action.

It is based on the assumption that biodiversity service provision, as a result of an action, is to some degree random and out of the control of the farmer or the agency. Smart weeding robots with selective weed removal abilities allow to deliberately set the level of biodiversity service provision which reflects an increase in the sensitivity of biodiversity to action. For an illustrative explanation of this parameter by means of existing schemes in Germany, please see Section 7.1 in the ODD protocol.

Based on the empirical evidence on the robots' removing abilities as described in Section 2, and following the original model, we assume a range of values from zero to 10, whereby high values reflect the use of robotic weeding.

Monitoring ability

In order to reflect the monitoring ability of novel weeding robots in the model, we consider three parameters: 1) detectability of biodiversity and of non-compliance, 2) agency monitoring costs, and 3) probability of farms being visited for non-compliance monitoring.

Given the empirical evidence on weeding robots' object detection performance in Section 2, we assume that through weeding robots, the detectability will increase which is captured in the model parameters dc, detectability of non-compliance with ABS rules and db, detectability of biodiversity. Similar to the original model, we assume a range of values for this parameter from zero to one, where high values reflect the use of robotic weeding.

Additionally, we assume that the availability of weeding robots will reduce the agency's monitoring costs (per hour). The model is set up such that the agency aims for a probability of detection of either biodiversity for RBS or non-compliance for ABS of 95%. The time needed to reach this value and the resulting costs depend strongly on how easily non-compliance and desired biodiversity can be detected and how costly it is to monitor for 1h. Following Schöttker et al. (2023), who evaluated the cost difference between human and drone-based monitoring for RBS, we conjecture a decrease in the pure monitoring costs. To reflect this change in the model, we consider a range of values for this parameter from zero to double the amount as in the original model.

Lastly, we assume that through the robot's monitoring ability the probability of farms (needed to) being visited for non-compliance monitoring by the agency changes. While in the original model set-up farms participating in an ABS need to be visited by agency employees in order to monitor their compliance with the scheme rules, we assume that under robotic weeding, this can be done by the robot. Therefore, we assume a range of values for this parameter whereby a value of "1" would reflect the case of robotic weeding as every farm's scheme compliance will be monitored but no longer through agency visits but by the robot.

Management costs

In order to reflect changes in the management costs associated with robotic weeding, we assume a broad range of values for parameter CL, the cost of setting the action to a certain level. However, the change can be in both directions and depends on various factors outside the model scope, such as production conditions, weed-yield dynamics, and farm characteristics (Shang et al. 2023; Yu et al. 2024). Therefore, we assume a range of values for this parameter spanning from zero to double the amount as assumed by Gibbons et al. (2011).

Table 4.1: Parameters reflecting assumptions on changes through weeding robots

Changes through robot (Sect. 2)	**Model parameters to reflect change (Sect. 3.2)**	**Assumed value ranges**	**Assumed direction through robot**	**Empirical foundation**
Selective weed removal	Sensitivity of biodiversity to action (*a*)	1/3–10 by 1/3	increase	Biodiversity gain and trade-off-reduction through weeding strategies at plant level of up to 80%. (Zingsheim & Döring, 2024)
Monitoring	Detectability of biodiversity (d_b) and of non-compliance (d_c)	0.1–1 by 0.1	increase	Improved monitoring abilities, e.g. mean average precision (mAP) as performance metric for object detection close to 90% (Salazar-Gomez et al., 2021; Weyler et al., 2024)
	Cost of agency monitoring (monetary unit/time unit) (C_h)	220 by 2	decrease	Difference in pure monitoring costs of UAV vs. human of ~1000€ per ha used as proxy (Schöttker et al., 2023)
	Only relevant to ABS			
	Probability of an agency visiting a farmer for non-compliance	0.1–1 by 0.2	increase[§]	Improved monitoring abilities, e.g. mean average precision (mAP) as performance metric for object detection close to 90% (Salazar-Gomez et

[§] If $P_v = 1$, this parameter becomes redundant as there is no longer a difference in monitoring costs between ABS and RBS.

	monitoring (P_v)			al., 2021; Weyler et al., 2024)
Manageme nt costs	Cost to farmer of setting the level of action to L (monetary unit) (C_L)	25–200 by 25	not clear, in- or decrease	Costs of robotic weed management depend on site-production and weed-dynamic specific characteristics (Lowenberg-DeBoer, Franklin, et al., 2021; Lowenberg-DeBoer et al., 2020; Shang et al., 2023; Yu et al., 2024)

4.4 Results and Discussion

4.4.1 *Biodiversity occurrence and gain*

Under ABS, farmers have to carry out the action at a predefined level, modelled as $L = 1$. In contrast under RBS, the farmer can flexibly decide on the optimal level that maximizes income. As shown in Figure 4.2, the probability that biodiversity occurs given scheme participation (red = low, purple = high) varies under ABS. It depends on the sensitivity of biodiversity to the action, *a* (different columns) and the probability that biodiversity already occurs in the field, P_0 (x-axis), while the level of action, *L* (y-axis) always remains at 1. Under RBS, the farmer can adjust the level of action, *L* and thereby balance low levels of the sensitivity of the action, *a*, and the low probability that biodiversity already occurs on the field, P_0, to maximize the probability that biodiversity occurs.

For both scheme types, the maximum probability of biodiversity occurrence of 1 is reached if the sensitivity is high (right column of Figure 4.2). In this scenario, RBS farmers perform the action at the minimal level needed to produce biodiversity, which is close to 0, given that the sensitivity is high. In reality, this action could, for example, be the use of a weeding robot that removes weeds based on the given indicators of the RBS (weed species, density and distribution), ensuring that the desired biodiversity occurs. The probability that biodiversity is already occurrent before scheme participation (x-axis) plays a more pronounced role if sensitivity is lower (left and middle columns of Figure 4.2). Due to the diminishing marginal returns to action, for RBS farmers, it might be profitable to execute the action at a level <1, given that P_0 is high, to reduce costs. The probability that biodiversity occurs might therefore be lower for RBS than ABS if the initial probability of biodiversity occurrence is high, as ABS farmers execute the action at L = 1 anyway.

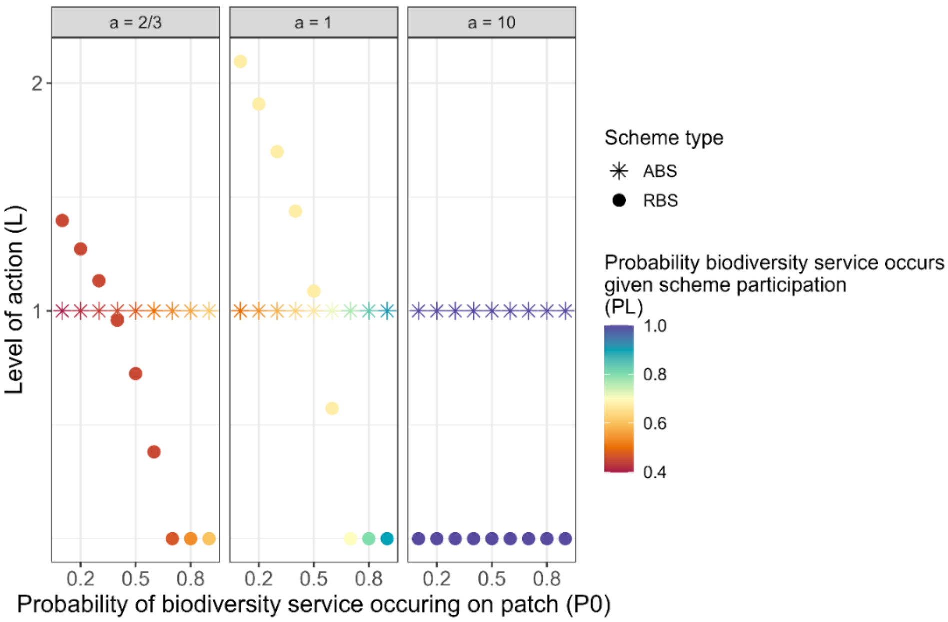

Figure 4.2: Probability that biodiversity service occurs given scheme participation by level of action (y-axis), three different levels of sensitivity of action (columns) and probability that the biodiversity service occurs before scheme participation (x-axis) for both scheme types.

Note: The probability that biodiversity service occurs given scheme participation, P_L, is depicted on a color scale, whereby purple indicates high levels for P_L (i.e. where PL is close to 1) and red indicates low levels (i.e. P_L is close to 0).

The resulting gain in biodiversity (G) is defined as the difference between the probability of biodiversity occurrence before and after scheme participation ($P_L - P_0$). It is therefore higher for RBS if the initial probability is low, slightly higher for ABS if the initial probability is high and similar for both scheme types with increasing sensitivity (Figure 4.3). For RBS, the full potential of biodiversity gain is exploited once the sensitivity to action is greater than 1.333. Recall that, by definition, the initial probability of biodiversity occurrence on the plot (P_0) and biodiversity gain (G) always sums up to 1, which implies that G is bounded, G < 1-P_0. In the case of ABS, farmers cannot balance the level of action and the sensitivity of the action. Hence, the biodiversity gain strongly depends on the initial biodiversity at the plot level, especially where sensitivity is low. With increasing sensitivity and increasing probability that biodiversity is already present before scheme participation, the difference in biodiversity gain between ABS and RBS vanishes (lower part of Figure 4.3), as both types of schemes exploit the full potential to increase the probability with which biodiversity occurs.

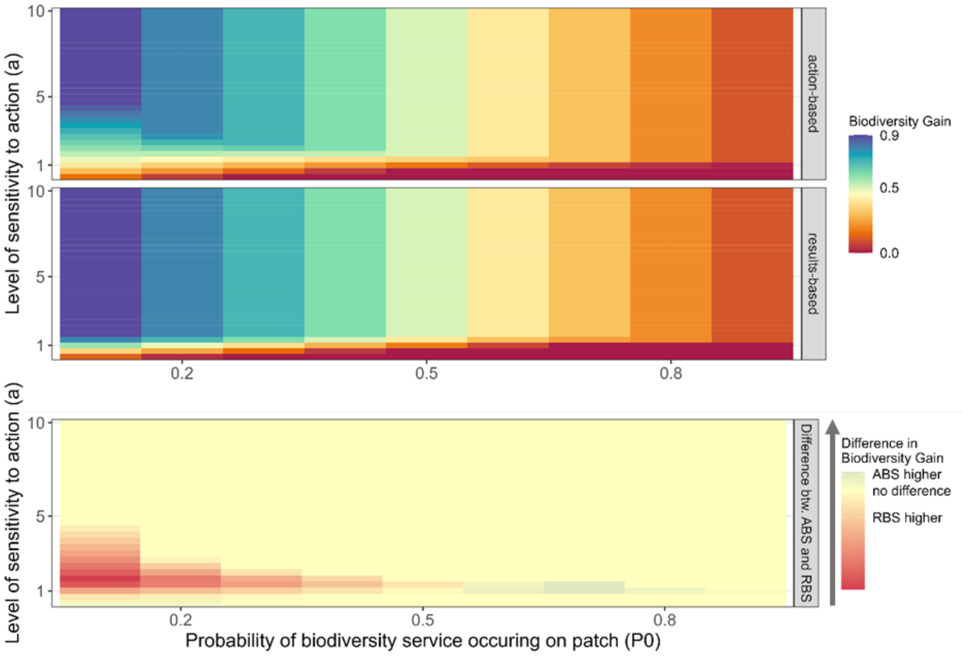

Figure 4.3: Biodiversity gain per scheme type (first row ABS, second row RBS) and difference between types (third row) by probability of biodiversity service occurring before scheme participation (x-axis) and level of sensitivity to action (y-axis).

Note: The gain in biodiversity, G, is depicted on a color scale, whereby purple indicates high levels (i.e. G is close to 1) red low levels (i.e. G is close to 0). When comparing ABS and RBS (third row), blue areas show where ABS are preferable (biodiversity gain is higher), red areas show where RBS are preferable and yellow areas show that the difference is (close to) 0. We added a grey arrow that indicates the direction of the effect when a weeding robot is used (see also the direction of effect in column 4 of Table 4.1).

From Figures 4.2 and 4.3, we conclude that ABS can produce higher biodiversity gains with increasing sensitivity to action. This is because, contrary to RBS, farmers cannot adjust the level of executing the action and balance out low sensitivity levels with higher action levels. Overall, this leads to an increase in and approximation of the biodiversity gains for both scheme types.

4.4.2 *Difference in efficiency between ABS and RBS*

To determine which scheme is preferable under various conditions, we now look at the difference in efficiency, that is, the biodiversity gain per agency expenditure. The gain in biodiversity depends on the sensitivity, the level of the action, and the initial probability for biodiversity occurrence (Figures 4.2 and 4.3). In contrast, the expenditures are composed of two parts: first, the payment to the farmer (D_L and D_P) and second, the costs for monitoring depending on the detectability, d and the resulting time, t, needed to detect either biodiversity or non-compliance at a sufficiently high rate (i.e. 0.95). For ABS, the payment is the same, independent of the gain in biodiversity. For RBS, the agency pays the farmer according to the probability that the benefit actually occurs. For an overview of expenditures by scheme type for selected parameter values, see Figure 4.10 and A 4.5 in the Appendix. As the two parameters a and d describe the characteristics of the weeding robot, while C_L, C_h and P_v refer to management and scheme conditions, we maintain three different levels for each of the former while varying those of the latter.

In Figure 4.4, we assume that the agency monitoring costs per time unit, C_h, vary between 2 and 20 monetary units. As noted above, the level of C_h mainly plays a role in efficiency, where monitoring makes up a large proportion of the agency expenditures (i.e., when detectability is low (left column)). Assuming that a weeding robot is available, we might end up in the lower-right corner, where the efficiency of both scheme types is similar, independent of the levels of C_h and P_0.

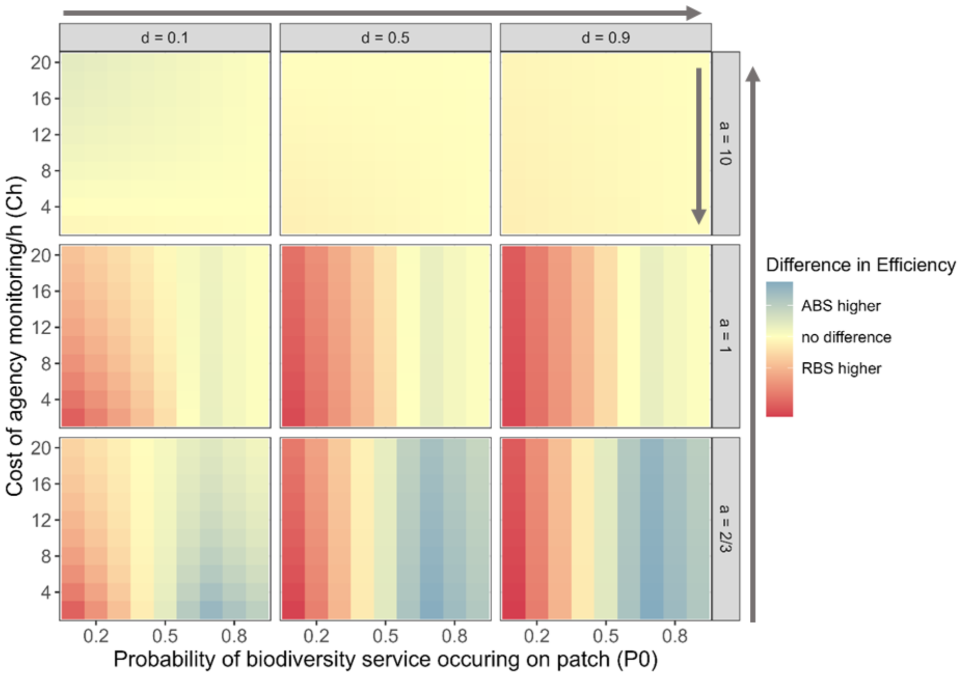

Figure 4.4: Relative differences in efficiency by sensitivity to action a (rows), detectability d (columns), probability of biodiversity service occurring on patch before scheme participation P_0 (x-axis) and agency monitoring costs C_h (y-axis).

Note: Blue areas show where ABS are preferable (efficiency is higher), red areas where RBS are preferable and yellow areas where the difference is (close to) 0. Grey arrows indicate the direction of the effect when a weeding robot is used (see also the direction of effect in column 4 of Table 4.1).

Next, we consider a range of values for the probability of farm visits P_v (Figure 4.5). An increasing probability of farms being visited for measuring non-compliance means that the difference in agency expenditures for monitoring between ABS and RBS is reduced. At a probability of 1, all farms participating in ABS are visited, which is the same extent as that of farms participating in RBS. We assume that, if a weeding robot does the monitoring, farms no longer need to be visited (which we reflect by assuming a low level of agency monitoring costs per time unit, C_h). Compliance would be monitored by the robot for all ABS-participating farmers (i.e. P_v = 1). Hence, there is no longer a difference between ABS and RBS with respect to monitoring costs. As expected, RBS gain in efficiency if ABS farms are visited with a higher probability, especially where detectability is low. In reality, the probabilities of farm visits ≤ 0.5

might increase non-compliance and are thus unrealistic; however, for completeness, we depict them here.

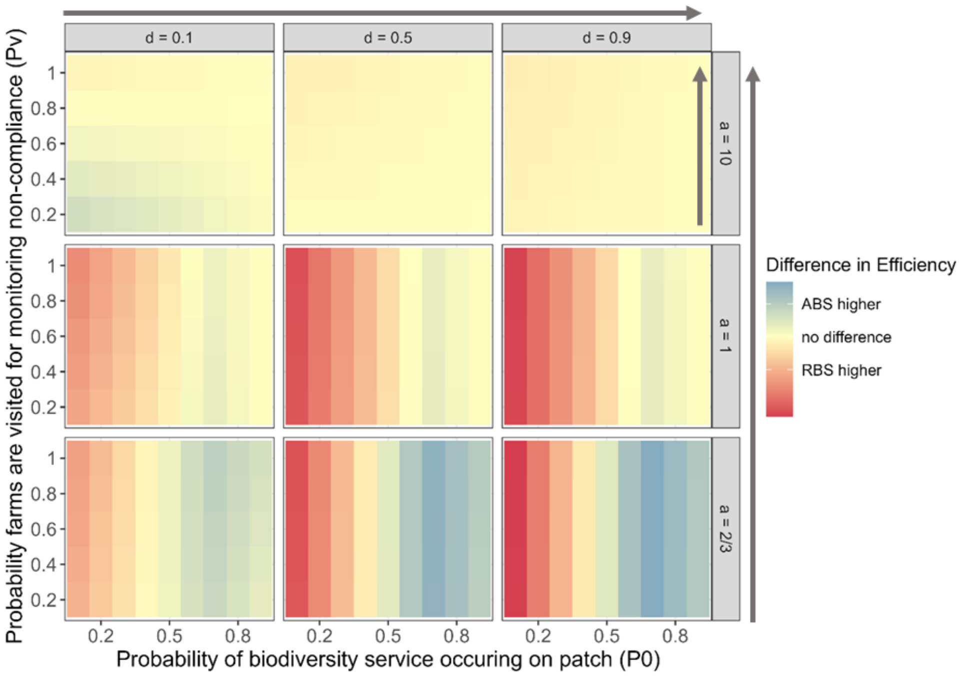

Figure 4.5: Relative difference in efficiency by sensitivity to action a (rows), detectability d (columns), probability of biodiversity service occurring on patch before scheme participation P_0 (x-axis) and probability of farm visits for monitoring non-compliance P_v (y-axis).

Note: Blue areas show where ABS are preferable (efficiency is higher), red areas where RBS are preferable and yellow areas show where the difference is (close to) 0. Grey arrows indicate the direction of the effect when a weeding robot is used (see also the direction of effect in column 4 of Table 4.1).

Finally, we turn to the cost of executing the action at a certain level, C_L (Figure 4.6). By construction, payments are proportional to the action costs and this parameter varies the proportion of agency expenditures that are spent on payments. With increasing action costs, differences in efficiency become smaller. This is because, for both scheme types, the costs rise to the same extent, meaning that with higher action costs, the proportion of the agency budget spent on payments increases and efficiency decreases. For low levels of action costs, the proportion of expenditures for monitoring drives the resulting efficiency, which explains why the difference in efficiency is more pronounced if detectability is high.

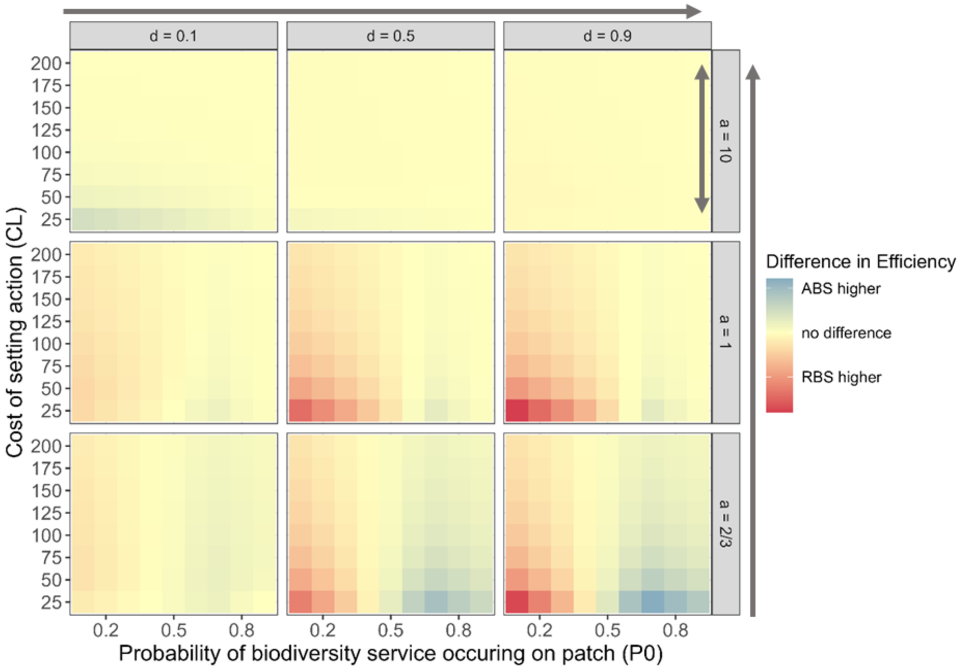

Figure 4.6: Relative difference in efficiency by sensitivity to action a (rows), detectability d (columns), probability of biodiversity service occurring on patch before scheme participation P_0 (x-axis) and costs of setting the action C_L (y-axis).

Note: Blue areas show where ABS are preferable (efficiency is higher), red areas where RBS are preferable and yellow areas show that the difference is (close to) 0. Grey arrows indicate the direction of the effect when a weeding robot is used (see also the direction of effect in column 4 of Table 4.1).

With increasing sensitivity to action, the difference in efficiency between ABS and RBS vanishes

We observe in all three panels of Figure 4.4, 4.5, and 4.6 that with increasing sensitivity, the difference in efficiency vanishes, independent of the other parameters that are considered. This is mainly the result of the full exploitation of biodiversity gains once the sensitivity is > $1.\overline{3}$ (Figures 4.2 and 4.3). Furthermore, the proportion of the agency budget spent on payments is high for both scheme types; for ABS, the payment is the same in any case, while in RBS, farmers are rewarded for delivering the full potential of the biodiversity benefit at a low level, hence lowering costs (see Figure 4.2, right column).

This finding challenges the current narrative of weeding robots as increasing the preferability of RBS due to their monitoring abilities (Besson et al., 2022; Finger, 2023). Our results show that ABS can also gain in efficiency, given the assumption that the weeding robots' removal abilities allow them to execute actions to which biodiversity is more sensitive, which calls for a discussion of the criticism of ABS as inefficient (Pe'er et al., 2020).

To translate this rather theoretical finding into concrete conservation efforts, we consider the results of Zingsheim and Döring (2024), who provide an idea of how such actions in terms of weeding strategies executed by a weeding robot could look. They explore the effects of different weeding strategies on several biodiversity parameters and yield. The authors find that the increase in biodiversity is the highest and the trade-off between yield and biodiversity is minimized, when weeding is based on (i) the number of species per area, (ii) thresholds for weed quantity (weed cover per species), and (iii) competitiveness of the weed with the crop based on Hunt et al. (2004)[**].

As an implication for future policy design, we conclude that not only the difference in efficiency between ABS and RBS vanishes, but also the difference in the overall design decreases. Given the weeding robot's removing and monitoring ability, future ABS could be set up such that farmers need to apply a certain weeding strategy on a plot (e.g., only weed every second row or only remove the most competitive weeds). Farmers could, ideally, simply download the software settings from the authorities to set up a certain strategy to comply with an ABS. Similarly, farmers could opt for these strategies as part of RBS and decide individually which weeds to remove or keep to reach the predefined target at the lowest cost. However, due to a lack of research, it remains difficult to foresee how specific these

[**] We hereby refer to information requirements for different weeding scenarios executed by weeding robots tested by Zingsheim and Döring (2024). Within the CSR strategy as developed by Hunt at al. (2004), weeds are categorized as strong (C-coordinate of 1) or weak (C-coordinate of 0) competitors. The underlying assumption is, that weeds which have a less competitive relation with crops can remain on the field, while the more competitive ones needs to be removed. In the resulting tested scenario "(9) Threshold ", uncompetitive weed species with a C-coordinate of 0 were left untreated.

findings might be for particular weed communities or at different spatial scales.

PES efficiency depends on the appropriately defined biodiversity indicators

The second pattern that occurs across the panels of Figure 4.4, 4.5 and 4.6 is the mediating role for the detectability of non-compliance (for ABS) and biodiversity (RBS), d, if sensitivity is ≤ 1. As the proportion of agency budget spent on monitoring depends strongly on detectability and the time needed to reach a detectability of 95%, costs are lower, and hence efficiency is higher, if detectability is high (right column).

However, while from a technical perspective, future weeding robots might be able to increase the detectability of biodiversity, the effect on scheme efficiency strongly depends on the actual biodiversity indicators chosen, which in turn depends on the scheme's goal, such as conservation of rare species vs. ecological resilience vs. biological pest control (Duelli and Obrist, 2003).

Within our model, we construct the indicator to be binary either in terms of whether species are present or not or in terms of whether a threshold on species abundance, distribution, and/or density is met or not. However, in reality, more complex indicator structures will be needed, taking also into account the biodiversity value of certain species, such as orchids in grassland as high-value species.

For either scheme type, it is crucial to define, from an ecological/biodiversity viewpoint, the appropriate *actions* (i.e., weeding strategies) and the appropriate *results* (i.e., biodiversity indicators) that could be considered within PES.

For RBS, it will no longer be enough to only define indicator species, but multidimensional indicators will be needed to prevent robots from outsmarting current RBS designs. If only a certain threshold for the number of species is given to receive a payment, robots might remove all but one individual of each indicator species. Thereby, the requirement is fulfilled at a very minimal level but an undesired outcome of a very low density of very homogeneously distributed weeds with only one individual per species is produced. Therefore, multidimensional composite indicators should also contain information on the desired density and distribution of weeds, as tested by Chaplin et al. (2021) and Šumrada et al. (2022), where a minimum weed density for the indicator species must be reached (for every *x* sections of a field) to receive the payment. However, while weeding robots might allow the inclusion of more sophisticated indicators, the actual choice of indicator *species*, their desired *density*, and their *distribution* would remain a major challenge for biodiversity research (Ruas et al., 2021; Zabel & Roe, 2009), and comes along with the problem of making biodiversity measurable in monetary terms (Bartkowski et al., 2015; Farnsworth et al., 2015).

For ABS, actions must be defined such that robots can easily monitor compliance. One example could be the strip wise removal of weeds in crops. Zingsheim and Döring (2024) show that this procedure can increase the gamma diversity of weeds at the field level. Hence, farmers could be rewarded for leaving certain strips or rows un-weeded, similar to a hypothetical (hybrid) scheme tested by Massfeller et al. (2022), an action that could be easily detected by the robot (Ahmadi et al., 2021).

Hence, because robots make it easier to monitor specific aspects of biodiversity and enable the definition of more precise actions, the actual choice and monetary valuation of indicators become more important. Defining these indicators and biodiversity aims clearly remains a task for future biodiversity research.

4.4.3 *Options arising from data on biodiversity status and gain*

Weeding robots might also open new options for designing novel policy schemes. Particularly, the possibility for the agency to have access to reliable data on biodiversity that existed on a plot before farmers joined a scheme, as well as data on the actual gains in biodiversity achieved through participation in the scheme (obtained via a robot) offer new possibilities.

First, we suppose that the status quo for biodiversity could be taken better into account for payments within RBS. Similar to Gibbons et al. (2011), we observe the importance of the probability of the biodiversity service being present before scheme participation for scheme efficiency. Data on biodiversity status and gain could be used to pay farmers in relation to capacity or proportional to the actual change (McDonald et al., 2018; D. Wang et al., 2023; Zabel & Roe, 2009). Such novel, probably more efficient, payment approaches could be combined with payments based on modelled results, as suggested by Bartkowski et al. (2021).

Second, such novel payment mechanisms could reduce farmers' (perceived) risk of not reaching the target, which currently constitutes a major barrier to adoption of RBS (Burton & Schwarz, 2013). This is because farmers would receive money for the (proportional) change considering the status quo and the capacity, or based on modelled results and no longer for either reaching or not reaching a pre-defined target that is the same for all farmers regardless of natural conditions. In particular, in view of increasing environmental risk through extreme weather events (Birthisel et al., 2021), novel payment structures must be further studied. We additionally expect that the risk of the biodiversity indicators not being detected, even when present, decreases through the increased detection ability of the weeding robot.

A third option concerns farmers' perceptions of biodiversity and scheme effects. Biodiversity conservation differs from other pro-environmental behaviors because measuring and perceiving biodiversity is difficult (Kidd et al., 2019; Kleijn et al., 2019). Furthermore, the environmental effects of weed management are hard to predict (Wilson et al., 2009). It has been noted that farmers who perceive positive environmental benefits from pesticide-free weeding tend to adopt this type of production (Möhring and Finger, 2022). Hence, it might prove relevant if weeding robots could communicate the measured biodiversity levels directly to the farmer. Therefore, not only might the perceived complexity of weed management effects decrease, but scheme acceptance could also increase (Moss, 2019; Wilson et al., 2009; Zwickle et al., 2014). In addition, these measured results could be communicated to the public or to other farmers as a form of signalling environmental engagement. This might be particularly relevant as social norms have been found to drive farmers' weed management decisions (Bakker et al., 2021; Burton & Wilson, 2006; Dentzman & Jussaume, 2017; Möhring et al., 2020).

4.4.4 *Recommendations for technology development*

From our findings, we derive recommendations for further technology development. We conclude that, besides focusing on weed removal efficiency (Merfield, 2023), technology development should also focus on the robots' other abilities that have been identified as crucial for scheme efficiency: 1) the reliable differentiation between various plant species (crops and weeds) in various growth stages and conditions, 2) the detection of compliance with ABS rules and 3) the ability to execute biodiversity-sensitive actions that allow selective removal of weeds, which should be closely linked to research on multidimensional indicators. Ideally, in the future, farmers would be able to simply download potential weeding strategies as ABS, directly from the agency to the robot.

Finally, throughout our study, we assume that in the future, data will be easily transferrable from robots to the agency (and back). This would allow for a decrease in transaction and monitoring costs and opens up possibilities to use the obtained data. However, the feasibility needs to be examined from a technical as well as a behavioral/data-protection perspective. For instance, farmers seem to be rather skeptical towards a 100% monitoring rate through novel technologies (Villanueva et al., 2024).

4.5 **Conclusion**

We find that the usage of weeding robots affects the optimal design for a payment for ecosystem services aiming at biodiversity conservation in arable farming in two ways. First, RBS gain efficiency through the weeding robots' monitoring ability. Second, ABS gain efficiency through weeding robots' ability to execute plant-individual actions to which the biodiversity might react more sensitively. We find these two effects to jointly eliminate the differences in efficiency between the two scheme types if detectability is high and biodiversity-sensitive actions can be performed. Thus, our results challenge the common belief that novel robots are mainly beneficial for RBS schemes. The monitoring ability of weeding robots has been conceptually considered in the literature, but we are the first to consider the potential effects of the weeding robot's selective removal ability on optimal PES design as well.

The main challenge for future policy design relates to the increased need for a clear definition of the desired biodiversity for both types of schemes. For ABS, appropriate actions with a high sensitivity need to be defined, whereas, for RBS, clear multi-dimensional indicators are necessary. The development of these actions and indicators needs to be supported by ecological research and carried out in close cooperation with technological development. However, defining these targets is challenging, and closing this research gap is a requirement for effective policymaking.

Our study assumes risk-neutral farmers and agencies. Future research could study how optimal robot-based PES designs would change under different risk preferences. Further, future research could investigate the options for novel payment schemes based on the obtained data on biodiversity. This might allow the inclusion of landscape considerations if payments depend on other farmers' performance in the same area (McDonald et al., 2018). Further, we do not include any social interactions in the model, although they influence farmers' decision-making. Future applications could build upon this study and include social aspects, especially with regard to schemes targeted at landscape scale, such as collaboration schemes (Schaub et al., 2023; Villamayor-Tomas et al., 2021).

Finally, we conclude that, by contrast to current narratives, the availability of weeding robots will not necessarily benefit only RBS efficiency. Given the option for more sensitive actions carried out by weeding robots, ABS can also remain a valuable instrument in the policy scheme toolbox.

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4.6 References

Ahmadi, Ahmadi, A., Halstead, M., McCool, C., 2022. BonnBot-I: A Precise Weed Management and Crop Monitoring Platform, in: 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). pp. 9202–9209.

Ahmadi, A., Halstead, M., McCool, C., 2021. Towards Autonomous Visual Navigation in Arable Fields. arXiv [cs.RO].

Ansell, D., Freudenberger, D., Munro, N., Gibbons, P., 2016. The cost-effectiveness of agri-environment schemes for biodiversity conservation: A quantitative review. Agric. Ecosyst. Environ. 225, 184–191.

Bakker, L., Sok, J., van der Werf, W., Bianchi, F.J.J.A., 2021. Kicking the Habit: What Makes and Breaks Farmers' Intentions to Reduce Pesticide Use? Ecol. Econ. 180, 106868.

Bartkowski, B., Droste, N., Ließ, M., Sidemo-Holm, W., Weller, U., Brady, M.V., 2021. Payments by modelled results: A novel design for agri-environmental schemes. Land use policy 102, 105230.

Bartkowski, B., Lienhoop, N., Hansjürgens, B., 2015. Capturing the complexity of biodiversity: A critical review of economic valuation studies of biological diversity. Ecol. Econ. 113, 1–14.

Basso, B., Antle, J., 2020. Digital agriculture to design sustainable agricultural systems. Nature Sustainability 3, 254–256.

Batáry, P., Dicks, L.V., Kleijn, D., Sutherland, W.J., 2015. The role of agri-environment schemes in conservation and environmental management. Conserv. Biol. 29, 1006–1016.

Batáry, P., Gallé, R., Riesch, F., Fischer, C., Dormann, C.F., Mußhoff, O., Császár, P., Fusaro, S., Gayer, C., Happe, A.-K., Kurucz, K., Molnár, D., Rösch, V., Wietzke, A., Tscharntke, T., 2017. The former Iron Curtain still drives biodiversity-profit trade-offs in German agriculture. Nat Ecol Evol 1, 1279–1284.

Bawden, O., Kulk, J., Russell, R., McCool, C., English, A., Dayoub, F., Lehnert, C., Perez, T., 2017. Robot for weed species plant-specific management. J. Field Robot. 34, 1179–1199.

Baylis, K., Peplow, S., Rausser, G., Simon, L., 2008. Agri-environmental policies in the EU and United States: A comparison. Ecol. Econ.

Beckmann, M., Gerstner, K., Akin-Fajiye, M., Ceaușu, S., Kambach, S., Kinlock, N.L., Phillips, H.R.P., Verhagen, W., Gurevitch, J., Klotz, S., Newbold, T., Verburg, P.H., Winter, M., Seppelt, R., 2019. Conventional land-use intensification reduces species richness and increases production: A global meta-analysis. Glob. Chang. Biol. 25, 1941–1956.

Berquer, A., Bretagnolle, V., Martin, O., Gaba, S., 2023. Disentangling the effect of nitrogen input and weed control on crop–weed competition suggests a potential agronomic trap in conventional farming. Agric. Ecosyst. Environ. 345, 108232.

Besson, M., Alison, J., Bjerge, K., Gorochowski, T.E., Høye, T.T., Jucker, T., Mann, H.M.R., Clements, C.F., 2022. Towards the fully automated monitoring of ecological communities. Ecol. Lett. 25, 2753–2775.

Biffi, S., Chapman, P.J., Engler, J.O., Kunin, W.E., Ziv, G., 2024. Using automated passive acoustic monitoring to measure changes in bird and bat vocal activity around hedgerows of different ages. Biol. Conserv. 296, 110722.

Birthisel, S.K., Clements, R.S., Gallandt, E.R., 2021. Review: How will climate change impact the 'many little hammers' of ecological weed management? Weed Res. 61, 327–341.

BMEL, 2023. Umsetzung der Gemeinsamen Agrarpolitik der Europäischen Union 2023 in Deutschland. Bundesministerium für Ernährung und Landwirtschaft .

Bolton, P., Dewatripont, M., 2004. Contract Theory. MIT Press.

Borgy, B., Gaba, S., Petit, S., Reboud, X., 2012. Non-random distribution of weed species abundance in arable fields. Weed Res. 52, 383–389.

Börner, J., Baylis, K., Corbera, E., Ezzine-de-Blas, D., 2017. The effectiveness of payments for environmental services. WORLD.

Brown, C., Kovács, E., Herzon, I., Villamayor-Tomas, S., Albizua, A., Galanaki, A., Grammatikopoulou, I., McCracken, D., Olsson, J.A., Zinngrebe, Y., 2021. Simplistic understandings of farmer motivations could undermine the environmental potential of the common agricultural policy. Land use policy 101, 105136.

Burton, R.J.F., Schwarz, G., 2013. Result-oriented agri-environmental schemes in Europe and their potential for promoting behavioural change. Land use policy 30, 628–641.

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

Campiglia, E., Radicetti, E., Mancinelli, R., 2018. Floristic composition and species diversity of weed community after 10 years of different cropping systems and soil tillage in a Mediterranean environment. Weed Res. 58, 273–283.

Canessa, C., Venus, T.E., Wiesmeier, M., Mennig, P., Sauer, J., 2023. Incentives, Rewards or Both in Payments for Ecosystem Services: Drawing a Link Between Farmers' Preferences and Biodiversity Levels. Ecol. Econ. 213, 107954.

Chaplin, S.P., Mills, J., Chiswell, H., 2021. Developing payment-by-results approaches for agri-environment schemes: Experience from an arable trial in England. Land Use Policy. https://doi.org/10.1016/j.landusepol.2021.105698

Connor, J.D., Ward, J.R., Bryan, B., 2008. Exploring the cost effectiveness of land conservation auctions and payment policies. Aust. J. Agric. Resour. Econ. 52, 303–319.

Dentzman, K., Jussaume, R., 2017. The Ideology of U.S. Agriculture: How Are Integrated Management Approaches Envisioned? Soc. Nat. Resour. 30, 1311–1327.

Derissen, S., Quaas, M.F., 2013. Combining performance-based and action-based payments to provide environmental goods under uncertainty. Ecol. Econ. 85, 77–84.

Duckett, T., Pearson, S., Blackmore, S., Grieve, B., Chen, W.-H., Cielniak, G., Cleaversmith, J., Dai, J., Davis, S., Fox, C., From, P., Georgilas, I., Gill, R., Gould, I., Hanheide, M., Hunter, A., Iida, F., Mihalyova, L., Nefti-Meziani, S., Neumann, G., Paoletti, P., Pridmore, T., Ross, D., Smith, M., Stoelen, M., Swainson, M., Wane, S., Wilson, P., Wright, I., Yang, G.-Z., 2018. Agricultural Robotics: The Future of Robotic Agriculture. arXiv [cs.RO].

Duelli, P., Obrist, M.K., 2003. Biodiversity indicators: the choice of values and measures. Agric. Ecosyst. Environ. 98, 87–98.

EC, 2023. Approved 28 CAP Strategic Plans (2023-2027). European Commission.

Ehlers, M.-H., Huber, R., Finger, R., 2021. Agricultural policy in the era of digitalisation. Food Policy 100, 102019.

Elmiger, B.N., Finger, R., Ghazoul, J., Schaub, S., 2023. Biodiversity indicators for result-based agri-environmental schemes – Current state and future prospects. Agric. Syst. 204, 103538.

European Commission, 2024. Integrated pest management (IPM) [WWW Document]. Food Safety. URL https://food.ec.europa.eu/plants/pesticides/sustainable-use-pesticides/integrated-pest-management-ipm_en (accessed 11.12.24).

European Commission, 2021. Key policy objectives of the new CAP [WWW Document]. Agriculture and rural development. URL https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/new-cap-2023-27/key-policy-objectives-new-cap_en (accessed 1.11.23).

Farnsworth, K.D., Adenuga, A.H., de Groot, R.S., 2015. The complexity of biodiversity: A biological perspective on economic valuation. Ecol. Econ. 120, 350–354.

Fennimore, S.A., Cutulle, M., 2019. Robotic weeders can improve weed control options for specialty crops. Pest Manag. Sci. 75, 1767–1774.

Ferraro, P.J., 2008. Asymmetric information and contract design for payments for environmental services. Ecol. Econ. 65, 810–821.

Finger, R., 2023. Digital innovations for sustainable and resilient agricultural systems. Eur. Rev. Agric. Econ. https://doi.org/10.1093/erae/jbad021

Garcia, V., McCallum, C., Finger, R., 2024. Heterogeneity of European farmers' risk preferences: an individual participant data meta-analysis. Eur. Rev. Agric. Econ. 51, 725–778.

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., Guerrero, I., Hawro, V., Aavik, T., Thies, C., Flohre, A., Hänke, S., Fischer, C., Goedhart, P.W., Inchausti, P., 2010. Persistent negative effects of pesticides on biodiversity and biological control potential on European farmland. Basic Appl. Ecol. 11, 97–105.

Gerhards, R., Weber, J.F., Kunz, C., 2020. Evaluation of weed control efficacy and yield response of inter-row and intra-row hoeing technologies in maize, sugar beet and soybean. Landtechnik 75, 247–260.

Gibbons, J.M., Nicholson, E., Milner-Gulland, E.J., Jones, J.P.G., 2011. Should payments for biodiversity conservation be based on action or results? J. Appl. Ecol. 48, 1218–1226.

Grimm, V., 2020. The ODD protocol: An update with guidance to support wider and more consistent use. Ecol. Modell. https://doi.org/10.1016/j.ecolmodel.2020.109105

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. Ecol. Modell. 198, 115–126.

Grimm, V., Railsback, S.F., Vincenot, C.E., Berger, U., Gallagher, C., DeAngelis, D.L., Edmonds, B., Ge, J., Giske, J., Groeneveld, J., Johnston, A.S.A., Milles, A., Nabe-Nielsen, J., Polhill, J.G., Radchuk, V., Rohwäder, M.-S., Stillman, R.A., Thiele, J.C., Ayllón, D., 2020. The ODD protocol for describing agent-based and other simulation models: A second update to improve clarity, replication, and structural realism. J. Artif. Soc. Soc. Simul. 23. https://doi.org/10.18564/jasss.4259

Guglielmini, A.C., Verdú, A.M.C., Satorre, E.H., 2017. Competitive ability of five common weed species in competition with soybean. Int. J. Pest Manage. 63, 30–36.

Hagemann, N., Gerling, C., Hölting, L., Kernecker, M., Markova-Nenova, N.N., Wätzold, F., Wendler, J., Cord, A.F., 2025. Improving result-based schemes for nature conservation in agricultural landscapes—challenges and best practices from selected European countries. Reg. Environ. Change 25. https://doi.org/10.1007/s10113-024-02324-2

Hole, D.G., Perkins, A.J., Wilson, J.D., Alexander, I.H., Grice, P.V., Evans, A.D., 2005. Does organic farming benefit biodiversity? Biol. Conserv. 122, 113–130.

Kidd, L.R., Garrard, G.E., Bekessy, S.A., Mills, M., Camilleri, A.R., Fidler, F., Fielding, K.S., Gordon, A., Gregg, E.A., Kusmanoff, A.M., Louis, W., Moon, K., Robinson, J.A., Selinske, M.J., Shanahan, D., Adams, V.M., 2019. Messaging matters: A systematic review of the conservation messaging literature. Biol. Conserv. 236, 92–99.

Kleijn, D., Bommarco, R., Fijen, T.P.M., Garibaldi, L.A., Potts, S.G., van der Putten, W.H., 2019. Ecological Intensification: Bridging the Gap between Science and Practice. Trends Ecol. Evol. 34, 154–166.

Kunz, C., 2017. Integrated weed control in sugar beet (Beta vulgaris), using precision farming technologies and cover cropping.

Kunz, C., Weber, J.F., Peteinatos, G.G., Sökefeld, M., Gerhards, R., 2018. Camera steered mechanical weed control in sugar beet, maize and soybean. Precis. Agric. 19, 708–720.

Landwirtschaftskammer, N.R.W., 2022. Biodiversitäts-Maßnahmen in der neuen Förderperiode ab 2023 [WWW Document]. URL https://www.landwirtschaftskammer.de/landwirtschaft/naturschutz/agrarreform/index.htm (accessed 1.11.23).

LANUV, 2023. Hellwegbörde Vogelschutzgebiet DE-4415-401 [WWW Document]. www.life-wiesenvoegel.nrw.de. URL https://www.life-wiesenvoegel.nrw.de/vogelschutzgebiete/hellwegboerde (accessed 4.1.23).

Li, N., Zhang, X., Zhang, C., Ge, L., He, Y., Wu, X., 2019. Review of Machine-Vision-Based Plant Detection Technologies for Robotic Weeding, in: 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, pp. 2370–2377.

Lindenmayer, D.B., Zammit, C., Attwood, S.J., Burns, E., Shepherd, C.L., Kay, G., Wood, J., 2012. A novel and cost-effective monitoring approach for outcomes in an Australian biodiversity conservation incentive program. PLoS One 7, e50872.

Lowenberg-DeBoer, J., 2019. The economics of precision agriculture, in: Precision Agriculture for Sustainability. Burleigh Dodds Science Publishing, pp. 481–502.

Lowenberg-DeBoer, J., Franklin, K., Behrendt, K., Godwin, R., 2021. Economics of autonomous equipment for arable farms. Precis. Agric. 22, 1992–2006.

Lowenberg-DeBoer, J., Huang, I.Y., Grigoriadis, V., Blackmore, S., 2020. Economics of robots and automation in field crop production. Precis. Agric. 21, 278–299.

Marshall, E.J.P., Brown, V.K., Boatman, N.D., Lutman, P.J.W., Squire, G.R., Ward, L.K., 2003. The role of weeds in supporting biological diversity within crop fields. Weed Res. 43, 77–89.

Massfeller, A., Meraner, M., Hüttel, S., Uehleke, R., 2022. Farmers' acceptance of results-based agri-environmental schemes: A German perspective. Land use policy 120, 106281.

McDonald, J.A., Helmstedt, K.J., Bode, M., Coutts, S., McDonald-Madden, E., Possingham, H.P., 2018. Improving private land conservation with outcome-based biodiversity payments. J. Appl. Ecol. 55, 1476–1485.

Merfield, C.N., 2023. Could the dawn of Level 4 robotic weeders facilitate a revolution in ecological weed management? Weed Res. 63, 83–87.

Merfield, C.N., 2016. Robotic weeding's false dawn? Ten requirements for fully autonomous mechanical weed management. Weed Res. 56, 340–344.

Meyer, S., Wesche, K., Krause, B., Leuschner, C., 2013. Dramatic losses of specialist arable plants in Central Germany since the 1950s/60s – a cross-regional analysis. Divers. Distrib. 19, 1175–1187.

Möhring, N., Finger, R., 2022. Pesticide-free but not organic: Adoption of a large-scale wheat production standard in Switzerland. Food Policy 106, 102188.

Möhring, N., Wuepper, D., Musa, T., Finger, R., 2020. Why farmers deviate from recommended pesticide timing: the role of uncertainty and information. Pest Manag. Sci. 76, 2787–2798.

Moreno, J.C., Berenguel, M., Donaire, J.G., Rodríguez, F., Sánchez-Molina, J.A., Guzmán, J.L., Giagnocavo, C.L., 2024. A pending task for the digitalisation of agriculture: A general framework for technologies classification in agriculture. Agric. Syst. 213, 103794.

Moss, S., 2019. Integrated weed management (IWM): why are farmers reluctant to adopt non-chemical alternatives to herbicides? Pest Manag. Sci. 75, 1205–1211.

Oerke, E.-C., 2006. Crop losses to pests. J. Agric. Sci. 144, 31–43.

Pandey, P., Dakshinamurthy, H.N., Young, S.N., 2021. Frontier: Autonomy in detection, actuation, and planning for robotic weeding systems. Trans. ASABE 64, 557–563.

Pannacci, E., Tei, F., 2014. Effects of mechanical and chemical methods on weed control, weed seed rain and crop yield in maize, sunflower and soyabean. Crop Prot. 64, 51–59.

Pe'er, G., Bonn, A., Bruelheide, H., Dieker, P., Eisenhauer, N., Feindt, P.H., Hagedorn, G., Hansjürgens, B., Herzon, I., Lomba, Â., Marquard, E., Moreira, F., Nitsch, H., Oppermann, R., Perino, A., Röder, N., Schleyer, C., Schindler, S., Wolf, C., Zinngrebe, Y., Lakner, S., 2020. Action needed for the EU Common Agricultural Policy to address sustainability challenges. People Nat (Hoboken) 2, 305–316.

Pe'er, G., Finn, J.A., Díaz, M., Birkenstock, M., Lakner, S., Röder, N., Kazakova, Y., Šumrada, T., Bezák, P., Concepción, E.D., Dänhardt, J., Morales, M.B., Rac, I., Špulerová, J., Schindler, S., Stavrinides, M., Targetti, S., Viaggi, D., Vogiatzakis, I.N., Guyomard, H., 2022.

How can the European Common Agricultural Policy help halt biodiversity loss? Recommendations by over 300 experts. Conserv. Lett. https://doi.org/10.1111/conl.12901

Peruzzi, A., Martelloni, L., Frasconi, C., Fontanelli, M., Pirchio, M., Raffaelli, M., 2017. Machines for non-chemical intra-row weed control in narrow and wide-row crops: a review. J. Agric. Eng. Res. 48, 57–70.

Rasch, S., Wünscher, T., Casasola, F., Ibrahim, M., Storm, H., 2021. Permanence of PES and the role of social context in the Regional Integrated Silvo-pastoral Ecosystem Management Project in Costa Rica. Ecol. Econ. 185, 107027.

RBPN, 2019. Country infos / Result Based Payments Network [WWW Document]. RBPN. URL https://www.rbpnetwork.eu/country-infos/ireland/protecting-farmland-pollinators-17/ (accessed 1.6.25).

Rose, D.C., Parker, C., Fodery, J., Park, C., Sutherland, W.J., Dicks, L.V., 2018. Involving stakeholders in agricultural decision support systems: Improving user-centred design. International Journal of Agricultural Management 06. https://doi.org/10.22004/ag.econ.287292

Ruas, S., Rotchés-Ribalta, R., hUallacháin, D.Ó., Ahmed, K.D., Gormally, M., Stout, J.C., White, B., Moran, J., 2021. Selecting appropriate plant indicator species for Result-Based Agri-Environment Payments schemes. Ecol. Indic. 126, 107679.

Salazar-Gomez, A., Darbyshire, M., Gao, J., Sklar, E.I., Parsons, S., 2021. Towards practical object detection for weed spraying in precision agriculture. arXiv [cs.CV].

Savary, S., Willocquet, L., Pethybridge, S.J., Esker, P., McRoberts, N., Nelson, A., 2019. The global burden of pathogens and pests on major food crops. Nature Ecology & Evolution 3, 430–439.

Schaub, S., Ghazoul, J., Huber, R., Zhang, W., Sander, A., Rees, C., Banerjee, S., Finger, R., 2023. The role of behavioural factors and opportunity costs in farmers' participation in voluntary agri-environmental schemes: A systematic review. J. Agric. Econ. https://doi.org/10.1111/1477-9552.12538

Scheper, J., Badenhausser, I., Kantelhardt, J., Kirchweger, S., Bartomeus, I., Bretagnolle, V., Clough, Y., Gross, N., Raemakers, I., Vilà, M., Zaragoza-Trello, C., Kleijn, D., 2023. Biodiversity and pollination benefits trade off against profit in an intensive farming system. Proc. Natl. Acad. Sci. U. S. A. 120, e2212124120.

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

Schöttker, O., Hütt, C., Jauker, F., Witt, J., Bareth, G., Wätzold, F., 2023. Monitoring costs of result-based payments for biodiversity conservation: Will UAV-assisted remote sensing be the game-changer? J. Nat. Conserv. 76, 126494.

Shang, L., Pahmeyer, C., Heckelei, T., Rasch, S., Storm, H., 2023. How much can farmers pay for weeding robots? A Monte Carlo simulation study. Precis. Agric. https://doi.org/10.1007/s11119-023-10015-x

Slaughter, D.C., Giles, D.K., Downey, D., 2008. Autonomous robotic weed control systems: A review. Comput. Electron. Agric. 61, 63–78.

Stein-Bachinger, K., Preißel, S., Kühne, S., Reckling, M., 2022. More diverse but less intensive farming enhances biodiversity. Trends Ecol. Evol. 37, 395–396.

Storm, H., Seidel, S.J., Klingbeil, L., Ewert, F., Vereecken, H., Amelung, W., Behnke, S., Bennewitz, M., Börner, J., Döring, T., Gall, J., Mahlein, A.-K., McCool, C., Rascher, U., Wrobel, S., Schnepf, A., Stachniss, C., Kuhlmann, H., 2024. Research priorities to leverage smart digital technologies for sustainable crop production. Eur. J. Agron. 156, 127178.

Šumrada, T., Japelj, A., Verbič, M., Erjavec, E., 2022. Farmers' preferences for result-based schemes for grassland conservation in Slovenia. J. Nat. Conserv. 66, 126143.

Thompson, C.R., Dille, J.A., Peterson, D.E., 2019. Weed competition and management in sorghum, in: Sorghum, Agronomy Monographs. Soil Science Society of America, Madison, WI, USA, pp. 347–360.

Tscharntke, T., Grass, I., Wanger, T.C., Westphal, C., Batáry, P., 2021. Beyond organic farming - harnessing biodiversity-friendly landscapes. Trends Ecol. Evol. 36, 919–930.

Villamayor-Tomas, S., Sagebiel, J., Rommel, J., Olschewski, R., 2021. Types of collective action problems and farmers' willingness to accept agri-environmental schemes in Switzerland. Ecosyst. Serv. 50, 101304.

Villanueva, A.J., Granado-Díaz, R., Colombo, S., 2024. Comparing practice- and results-based agri-environmental schemes controlled by remote sensing: An application to olive groves in Spain. J. Agric. Econ. https://doi.org/10.1111/1477-9552.12573

Walter, A., Khanna, R., Lottes, P., Stachniss, C., Siegwart, R., Nieto, J., Liebisch, F., 2018. Flourish-a robotic approach for automation in crop management. Proceedings of the international conference on precision agriculture (ICPA).

Wang, D., Gurhy, B., Hanusch, M., Kollenda, P., 2023. Could Sustainability-Linked Bonds Incentivize Lower Deforestation in Brazil's Legal Amazon? https://doi.org/10.2139/ssrn.4567384

Wätzold, F., Jauker, F., Komainda, M., Schöttker, O., Horn, J., Sturm, A., Isselstein, J., 2024. Harnessing virtual fencing for more effective and adaptive agri-environment schemes to conserve grassland biodiversity. Biol. Conserv. 297, 110736.

Weyler, J., Magistri, F., Marks, E., Chong, Y.L., Sodano, M., Roggiolani, G., Chebrolu, N., Stachniss, C., Behley, J., 2024. PhenoBench: A large dataset and benchmarks for semantic image interpretation in the agricultural domain. IEEE Trans. Pattern Anal. Mach. Intell. PP, 1–12.

White, B., Hanley, N., 2016. Should We Pay for Ecosystem Service Outputs, Inputs or Both? Environ. Resour. Econ. 63, 765–787.

Wilson, R.S., Hooker, N., Tucker, M., LeJeune, J., Doohan, D., 2009. Targeting the farmer decision making process: A pathway to increased adoption of integrated weed management. Crop Protection. https://doi.org/10.1016/j.cropro.2009.05.013

Wu, X., Aravecchia, S., Lottes, P., Stachniss, C., Pradalier, C., 2020. Robotic weed control using automated weed and crop classification. J. field robot. https://doi.org/10.1002/rob.21938

Wunder, S., Engel, S., Pagiola, S., 2008. Taking stock: A comparative analysis of payments for environmental services programs in developed and developing countries. Ecol. Econ. 65, 834–852.

Young, S.L., 2018. Beyond Precision Weed Control: A Model for True Integration. Weed Technol. 32, 7–10.

Yu, C., Khanna, M., Atallah, S.S., Kar, S., Bagavathiannan, M., Chowdhary, G., 2024. Herbicide-resistant weed management with robots: A weed ecological–economic model. Agric. Econ. https://doi.org/10.1111/agec.12856

Zabel, A., Roe, B., 2009. Optimal design of pro-conservation incentives. Ecol. Econ. 69, 126–134.

Zhang, W., Miao, Z., Li, N., He, C., Sun, T., 2022. Review of Current Robotic Approaches for Precision Weed Management. Curr Robot Rep 3, 139–151.

Zimdahl, R.L., 2007. Weed-Crop Competition: A Review. John Wiley & Sons.

Zingsheim, M.L., Döring, T.F., 2024. What weeding robots need to know about ecology. Agric. Ecosyst. Environ. 364, 108861.

Zwickle, S., Wilson, R., Doohan, D., 2014. Identifying the challenges of promoting ecological weed management (EWM) in organic agroecosystems through the lens of behavioral decision making. Agric. Human Values 31, 355–370..

4.7 **Appendix**

4.7.1 *A. Sensitivity Analysis of parameter x*

We conduct a sensitivity analysis for the parameter x, that describes the multiple of the costs paid to the farmer as payment by the agency. For a detailed examination of the optimal level of x see also Figure S3 in the supplementary material in Gibbons et al. (2011).

While we assume a fixed level for x of 10 for the analysis in the main paper, we here explore how for different levels of x the probability of biodiversity service occurrence (Figure 4.7), the gain in biodiversity (Figure 4.8) and the difference in efficiency between scheme types (Figure 4.9) vary.

As can be seen in Figure 4.7, the probability of biodiversity service occurring under scheme participation remains the same for ABS for different levels of x as farmers do not change their level of action. Contrarily, for RBS, the level of x makes a difference in the probability of biodiversity service provision, as for higher levels of x, farmers are willing to increase their levels of action while for lower levels of x, they decrease it. For low levels of sensitivity to action, a, (left column), ABS can increase the probability of biodiversity service occurrence more as farmers execute the action still at level 1. With increasing levels of sensitivity to action (middle and right column) and increasing payment (lower rows), RBS exhibit higher probabilities of biodiversity service occurrence. The same phenomenon can be observed in Figure 4.8. Here also, the role of the initial biodiversity service occurrence on the plot is emphasized.

In Figure 4.9, we compare the difference in efficiency given different levels of x and selected levels of Ch, Pv, and CL. The pattern remains the same as in Figures A 4.1 and A 4.2, but at different intensities depending on the level of the other variables influences scheme efficiency.

We conclude that given restricted agency budgets and, hence, rather low payments, the sensitivity of the action has to be carefully considered when deciding on whether to offer farmers ABS or RBS. Overall, RBS might prove more efficient, but for low payments and low sensitivity, farmers might execute actions at very low levels, thereby not leading to the desired increase in biodiversity service occurrence.

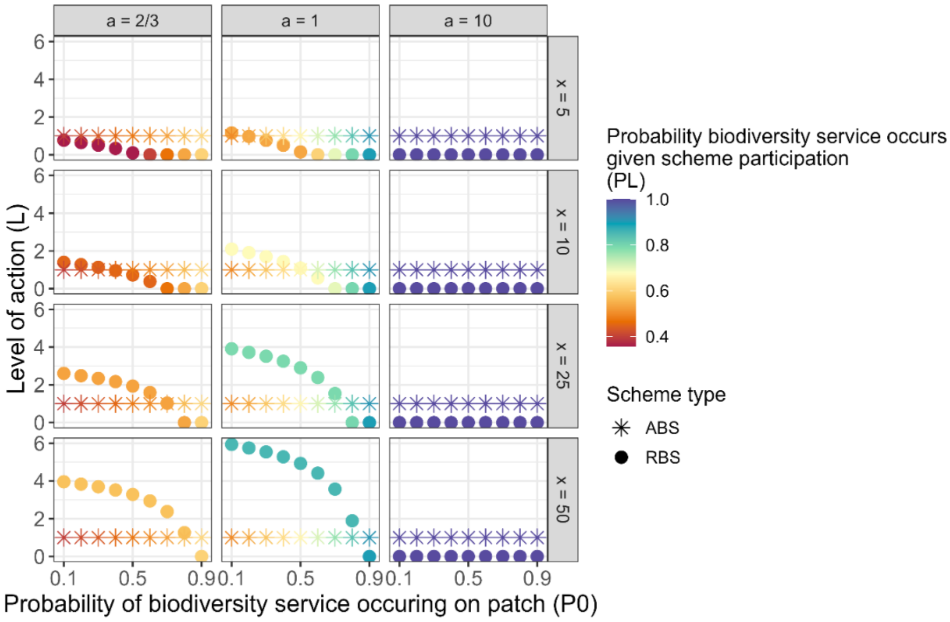

Figure 4.7: Probability of biodiversity occurring under scheme participation for different levels of x

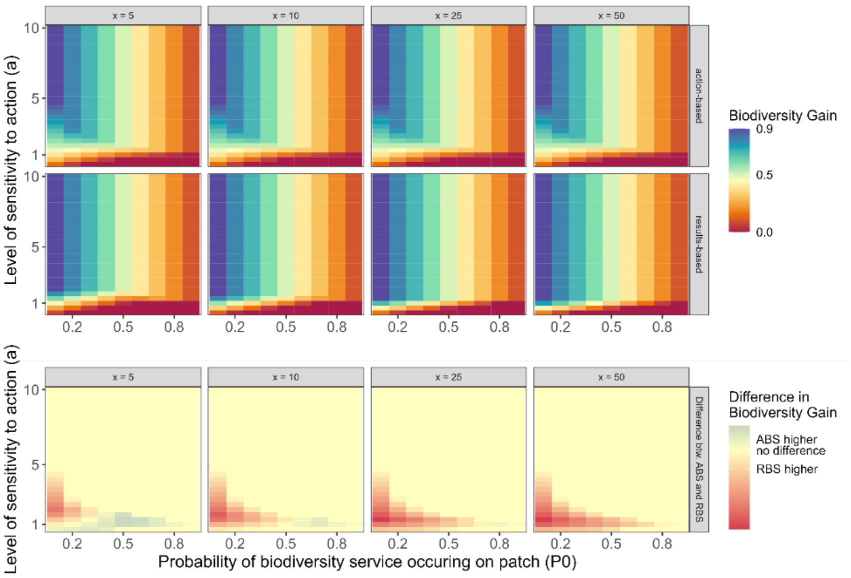

Figure 4.8: Gain in biodiversity and difference between scheme types for different levels of x

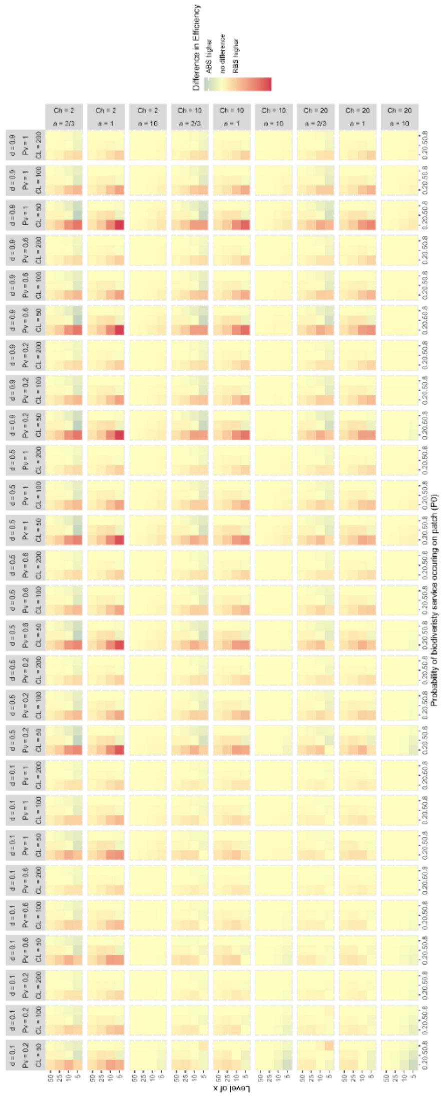

Figure 4.9: Difference in efficiency for different levels of x, Pv, Ch and CL

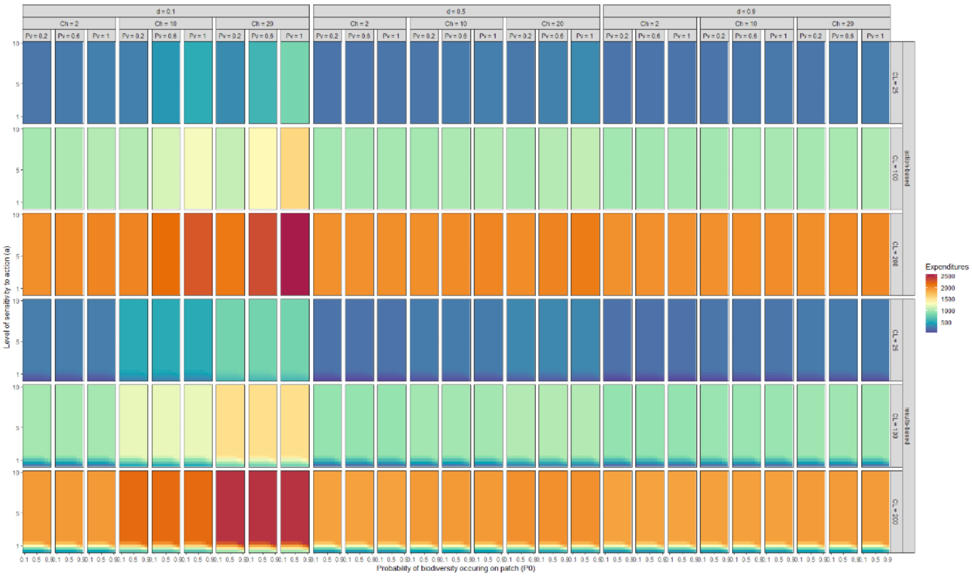

Figure 4.10: Agency expenditures for both scheme types by selected values for all parameters

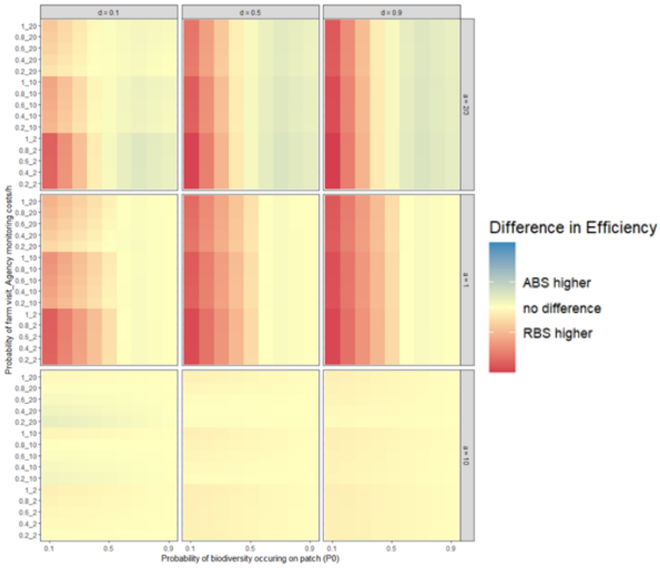

Figure 4.11: Difference in efficiency by parameters related to monitoring costs (i.e. Ch, Pv and d).

Note that on the y-axis we depict two parameters: Pv and Ch. For each selected value of Pv (0.2, 0.4, 0.6, 0.8, 1) three different values for Ch are assumed (2,10,20)