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Notwendige Fragen

Das Gewicht der Angst

Die Länge und Breite der Liebe

Die Farbe der Sehnsucht

im Schatten und in der Sonne

Wie viel Steine geschluckt werden müssen

als Strafe für Glück

und wie tief man graben muss

bis der Acker Milch gibt und Honig

Erich Fried

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Kurzfassung

Landwirtschaftliche Innovationen im Allgemeinen und Smart Farming Technologien (SFT) im Speziellen haben das Potenzial, negative Umwelteffekte und die damit verbundenen Risiken moderner landwirtschaftlicher Praktiken zu mindern, während sie deren Produktivität und Präzision steigern. Für Technologiehersteller, Agrarökonomen und politische Interessenvertreter ist es von zentraler Bedeutung, ein umfassendes Verständnis der Treiber der Technologieannahme zu entwickeln und zu verstehen, warum Landwirte weiterhin zögern, sich mit intelligenten und autonomen Technologien zu befassen, um das volle Potenzial dieser nachhaltigen Innovationen zu entfalten.

Diese Dissertation untersucht die Annahme landwirtschaftlicher Innovationen aus verschiedenen Blickwinkeln. Zunächst identifizieren und ordnen wir quantitative Literatur zur Annahme landwirtschaftlicher Innovationen systematisch in einer globalen Evidence Map von beträchtlicher Größe an, um die statistische Relevanz von häufig und weniger häufig untersuchten Determinanten der Technologieannahme zu untersuchen und um daraus Forschungsempfehlungen abzuleiten. Wir gehen dann im Rahmen eines Lab-in-the-Field Experiments genauer auf die Haltungen deutscher Ackerbauern gegenüber SFT ein und testen explizit, ob ausgewählte hypothetische Politikszenarien einen positiven Effekt auf deren zukünftige Annahmebereitschaft haben. Ferner replizieren wir dieses Experiment mit landwirtschaftlichen Studierenden, um ein unerwartetes Verhaltensmuster genauer zu untersuchen, das in obigem Experiment mit Ackerbauern entdeckt wurde. Außerdem leiten wir daraus eine Aussage über Effekte ab, die sich potenziell durch die Wahl spezifischer Teilnehmergruppen in experimentellen Stichproben erklären lassen. Zuletzt nutzen wir ein psychologisches Konzept—die Theory of Planned Behahvior (TPB)—zur Erforschung der Rolle zusätzlicher ausgewählter Verhaltensparameter hinsichtlich der Intention der Landwirte, Spot Spraying zu Herbizid reduzierter Beikrautregulierung auf ihren eigenen Feldern zu nutzen.

Während wir global häufig erforschte soziodemografische und Strukturvariablen statistisch zumeist als insignifikant beobachten, finden wir, dass seltener untersuchte Variablen mit Bezug zum Verhalten von Landwirten, deren persönlichen Einstellungen und Interaktion mit ihrem sozialen und professionellen Umfeld relativ betrachtet höhere

statistische Relevanz in der Annahmeforschung zu haben scheinen. Diese Erkenntnisse werden durch die Ergebnisse der experimentellen und der TPB Studie ergänzt. Im Speziellen sind die positive Umwelteinstellung und Innovationsfreude der Landwirte starke Prädikatoren ihrer SFT Annahmeintentionen. Weitere aussagekräftige Verhaltensparameter des Vorhabens, Spot Spraying auf den eigenen Feldern innerhalb der nächsten fünf Jahre zu nutzen, sind soziale Normen und Moralempfinden der Landwirte bezogen auf einen pfleglichen Umgang mit der Umwelt. Allerdings finden wir für keins der hypothetischen Politikszenarien den erwarteten statistischen Effekt, obwohl sowohl die Richtung als auch die Magnitude der Schätzer im Sinne der Hypothesen vielversprechend ausfallen. Darüber hinaus finden wir deutliche Unterschiede zwischen den Ergebnissen aus den Stichproben mit Landwirten und Studierenden, was Zweifel an der Eignung von Studierenden als Substitute für Landwirte in Experimenten bezüglich erwartbarer Effekte von Agrarpolitiken nahelegt.

Neben den methodischen und theoretischen Beiträgen dieser Dissertation verdeutlichen insbesondere unsere Ergebnisse die Relevanz von Verhaltensparametern für zukünftige Forschungsbestreben sowie kontextbezogene Agrarpolitikstrategien mit dem Ziel einer nachhaltigen Intensivierung der modernen Landwirtschaft.

Schlüsselwörter: *Annahme landwirtschaflticher Innovationen, Smart Farming Technologien, Farmebene, Verhaltensdeterminanten, Auswertung hypothetischer Politikszenarien, experimentelle Methoden*

Abstract

Agricultural innovations in general and smart farming technologies (SFT) in particular, can mitigate the negative environmental impacts and risk inherent to modern agricultural practices while increasing productivity and precision thereof. Clearly, understanding what drives their adoption and why farmers are still hesitant to venture into the field of smart and autonomous farming technologies is pivotal for technology producers, agricultural economists and political stakeholders alike to unfold the full potential of these sustainable innovations.

The present dissertation studies the adoption of agricultural innovations from different vantage points. First, we systematically identify and organize quantitative agricultural innovation adoption literature in a sizable global evidence map to learn about the statistical relevance of frequently and less frequently investigated farm-level adoption determinants and to propose future avenues of research. Second, in a framed lab-in-the-field experiment with German crop farmers we delve deeper into their attitudinal dispositions toward SFT, and we test whether a set of hypothetical policy scenarios has a positive effect on farmers' intention to use more SFT in the future. Third, we replicate the above experiment with agricultural students to get a better understanding of an unexpected behavioral pattern observed in the farmer sample and to derive a statement regarding potential subject pool effects in agricultural policy evaluation studies. Fourth and last, we draw on a psychological framework—the Theory of Planned Behavior (TPB)—to extend our knowledge regarding likely behavioral antecedents of farmers' intention to use spot spraying for herbicide-reduced weed control on their own farms.

While frequently investigated structural and sociodemographic variables are found statistically insignificant in a vast majority of studies investigating adoption across the globe, less frequent variables pertaining to farmers' behavior, attitudes and their embeddedness in their social and professional environment bear statistical relevance for adoption relatively more often. This is complemented by the findings of both the experimental and the TPB approaches. In particular, farmers' pro-environmental attitude and innovativeness are found to be strong predictors of their intended SFT adoption. In addition, social and moral norms to tend to the environment render themselves

relevant antecedents of farmers intention to conduct weed management via spot spraying technology on their own fields within the next five years. By contrast, neither of the investigated policy scenarios yield the expected effects on SFT adoption intention. Promisingly, however, both their magnitude and direction of effect are in line with theoretical predictions. We can further show a marked discrepancy between the results derived from the farmers and students, respectively, which casts doubt on the adequacy of using agricultural students as substitutes for farmers in agricultural policy evaluation experiments.

The methodological and theoretical contributions alongside the insights derived in this dissertation emphasize the relevance of behavioral determinants to inform future research endeavors and enable context-specific agricultural policies aiming at sustainable intensification of modern agriculture.

Keywords: *agricultural innovation adoption, smart farming technologies, farm-level, behavioral determinants, hypothetical policy scenario evaluation, experimental methods*

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List of Abbreviations

AI	**A**rtificial **I**ntelligence
APE	**A**verage **P**artial **E**ffect
AttEnv	Pro-**env**ironmental **att**itude
AttSS	**A**ttitude toward **S**pot **S**praying
BC	**B**road**c**ast application
BRICS	Intergovernmental organization of states of **B**razil, **R**ussia, **I**ndia, **C**hina **S**outh Africa
DT	**T**rust in farming **d**ata security and privacy
DIT	**D**ual **I**nterest **T**heory
FMNL	**F**ractional of **M**ulti**n**omial **L**ogit
INT	**Int**ention to use Spot Spraying
KTBL	**K**uratorium für **T**echnik und **B**auwesen in der **L**andwirtschaft e.V.
MEF	**M**eta**e**conomics **F**ramework
MN	**M**oral **N**orms
NRW	**N**orth **R**hine-**W**estphalia
OECD	**O**rganisation for **E**conomic **C**o-operation and **D**evelopment
PCB	**P**erceived **B**ehavioral **C**ontrol
PI	**P**ersonal **i**nnovativeness
PLS-SEM	**P**artial **L**east **S**quares **S**tructural **E**quation **M**odeling
QMLE	**Q**uasi-**m**aximum **l**ikelihood **e**stimation procedure
SD	**S**tandard **D**eviation
SFT	**S**mart **F**arming **T**echnology
SMS	**S**hort **M**essage **S**ervice
SN	**S**ubjective **N**orms
SRMR	**S**tandardized **R**oot **M**ean **S**quare **R**esidual
SS	**S**pot **S**praying
SWT	**S**mart **W**eeding **T**echnology
TPB	**T**heory of **P**lanned **B**ehaviour
VIF	**V**ariance **I**nflation **F**actor
WR	**W**eeding **R**obot

Chapter 1

Research context[1]

1.1 Motivation and structure

The challenges for global agricultural systems are numerous. A continuous growth of the global population (United Nations, 2021) alongside the anticipated increase in global demand for food, feed, and fiber (van Dijk et al., 2021; von Braun et al., 2021) will require a transformation of agriculture to achieve greater levels of productivity while reducing negative impacts on biodiversity, ecosystems, and climate (Garnett et al., 2013). The societal relevance of this notion has led international organizations and governmental institutions to proclaim multi-annual agendas for global sustainable development (United Nations, 2023) and formulate specific goals, such as the pan-Europe target, to reduce pesticides by 50% until 2030 (European Union, 2020). However, unfavorable trends with respect to biodiversity (Hallmann et al., 2017), ecosystems quality (Newbold et al., 2015), the intensity of pesticide use (FAOSTAT, 2024) and the availability of agricultural land in developed countries such as Germany (Destatis, 2024), have made sustainable intensification of farming a particularly ambitious endeavor.

Innovations in farm management processes and technology are seen as a crucial element to increase profitability of farming and promote sustainable intensification by improving the efficiency of input use, reducing agricultural greenhouse gas emissions, lowering natural resource exploitation, and mitigating adverse impacts on ecosystems in water and on land (Springmann et al., 2018). In particular, recent developments of smart

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farming technologies (SFT) are considered pivotal innovations, with the potential to fundamentally transform farming systems and harmonize the outlined trade-offs inherent to agricultural production (Lindblom et al., 2017; Walter et al., 2017). Aerial modes of operation, smart sensors, and artificial intelligence (AI) enable unprecedented resolution and speed of agronomic data collection and analysis in real time to inform farmers' managerial processes. This enables machine-based high-precision application of inputs tailored to the spatiotemporal requirements of field sections or even individual plants (Aubert et al., 2012; Wolfert et al., 2017). This can substantially reduce washout of chemical inputs into the environment (Finger et al., 2019). Moreover, increasing levels of automation can reduce human labor requirements and alleviate physical working conditions (Bovensiepen et al., 2016; Finger, 2023).

The anticipated consequences ascribed to innovation-based sustainable intensification of agriculture clearly transcend the boundaries of individual farming operations. Especially the expected environmental improvements bear a public good character as they benefit society at large. From the perspectives of political decision makers and advisers, agricultural economists, and non-governmental interest groups, it is thus of high interest to understand what drives and hinders the adoption process on farm level. This knowledge can inform the design of enabling policy strategies to accelerate the diffusion and eventually exploit the full potential of societally highly beneficial innovations. Situated in this interplay of interests, the present dissertation has the overarching objective to investigate what drives the uptake of eco-friendly agricultural innovations with a particular consideration of SFT, for which the empirical research basis is yet scarce. While each chapter avails itself of a different research methodology, the focal vantage point remains with farmers as the adopting entity throughout the entire dissertation. We study farmers' behavioral dispositions and thereby do not only contribute to painting a more holistic picture of potentially relevant adoption determinants. We also draw on and extend experimental approaches to test potential policies to pave the way toward a more evidence-based promotion of sustainable intensification of agriculture.

The determinants of the uptake of more productive, environmentally conserving, and less risky agricultural innovations have been studied for decades. The current body of quantitative observational literature accumulates to a vast amount of farm-level studies to investigate the association of farmers' adoption behavior with a multitude of economic, demographic, and contextual variables. To retain an overview of the abundant literature and to facilitate the design of policies to promote innovation uptake, scholars have conducted meta-analyses with varying methodological approaches and thematic perspectives. The majority thereof, however, are inconclusive, and it needs to be assumed that adoption might be highly specific to individual innovation types and contexts. What is more, economic and sociodemographic variables are strongly overrepresented, while measures of farmers' behavior, their network, or specific attributes of the innovations themselves were relatively underrepresented (de Oca Munguia and Llewellyn, 2020; Thompson et al., 2023). The objective of Chapter 2 is therefore to establish an updated global evidence map of the available agricultural innovation adoption literature to address the prevalent inconclusiveness thereof. In depicting their frequency and statistical relevance, the primary aim of this chapter is to formulate unequivocal statements regarding the impact of common adoption determinants and identify ambiguous and poorly researched determinant categories to formulate priorities for future research.

The body of empirical adoption literature with a focus on SFT is much less abundant. This is largely owed to the fact that these innovations are still in an early stage of technological development with little commercial availability. While their value proposition has previously been recognized by scientists from different disciplines (e.g., Balafoutis et al., 2017; Lowenberg-DeBoer et al., 2020; Weersink et al., 2018), the expected benefits revolving around gains in profitability and input-use efficiency next to the mitigation of environmental impacts remain widely unexploited due to faltering rates of adoption and diffusion. Furthermore, open questions pertaining to novel SFT features, e.g., AI, autonomous modes of operation and data collection concern potential adopters (e.g., Jakku et al., 2019; Sparrow and Howard, 2021). Studying how novel technology characteristics correspond to and interact with farmers' non-monetary personal motives may thus complete and potentially adjust our conceptualization of agricultural technology adoption (Blasch et al., 2022; Chouinard et al., 2008; Kuehne et al., 2017; Musshoff and Hirschauer, 2014). This sets the scene for Chapter 3 in which we investigate German crop farmers' intended SFT adoption in a framed lab-in-the-field experiment. The first objective is to learn how farmers' attitudes toward the environment and innovations, next to their trust in the security and sovereignty of agricultural data collected by autonomous robots, co-determine willingness to adopt SFT. The second objective is to find out whether a set of realistic policy scenarios can positively influence farmers' intended adoption in a positive way. With this artificial experimental setting we are not only able to investigate highly relevant behavioral determinants of SFT adoption (Dessart et al., 2019) but we also provide a cost-efficient approach to evaluate policy strategies to support farmers who want to contribute to transforming modern agriculture in a more sustainable direction through the use of these innovations.

To elicit farmers' intended SFT adoption, the experimental centerpiece of Chapter 3 is a two-round business simulation game (cf. Thomas et al., 2019). Among other things, we therein tested the effect of three hypothetical policy treatments on farmers' SFT adoption behavior compared to a control group. The results reveal an unexpected phenomenon: The control group, despite not having received a treatment, exhibited a behavior change from round one to round two in the sense of the policy treatments, which strongly resembles the behavior change of the treatment groups. We argue in Chapter 3 that this "round effect" may be a reason why no statistically significant effect was found for any of the policies. This finding motivated Chapter 4, in which we describe and discuss an adapted experimental design and the results of a replication of the above lab-in-the-field experiment with German agricultural students. The specific objective was to find out whether the round effect is an artifact and therefore specific to the farmer sample in Chapter 3, or whether it is the result of a methodological issue inherent to multi-period (agricultural) economic management games. In any case, learning about round effects is of high relevance for policy makers and agricultural economists, who interpret and implement findings from similar experimental approaches into policy designs, and it would require accommodating round effects in future research. As such, Chapter 4, in its brevity, is a methodological amendment to the objective of this dissertation. It aims to shed light on a phenomenon in experimental research which is, to the best of our knowledge, little known and understood in this field.

This dissertation concludes with Chapter 5. It presents a purely behavioral approach to studying German farmers' intended adoption of one exemplary SFT, namely spot spraying for herbicide-reduced weed management. The chapter is thus an immediate response to the findings in Chapter 2 and to the pleas of previous authors to place greater attention on behavioral variables (Dessart et al., 2019; Thomas et al., 2019; Thompson et al., 2023). Arguably, this may uncover more subtle, context-specific influences on farmers' technology uptake, which has long been analyzed through the lens of profit maximization (Musshoff and Hirschauer, 2014). We build on the Theory of Planned Behavior (TPB) (Ajzen, 1991), a psychological theory which is not based in the paradigm of rational decision-making (Sok et al., 2021). Briefly, this theory predicts an individual's intended actions by their attitude toward the action, the feeling of being in control and capable of the action, and the influence of their personal environment of, e.g., colleagues or peers. Our first objective was to test and adapt this theory in the context of farmers' spot spraying adoption decision. The second objective was to test an extended version of the theoretical framework to capture the extent to which farmers' affinity to innovations alongside their environmental and moral dispositions function as behavioral antecedents of their attitude toward spot spraying and the intention to adopt it. In sum, the objective of Chapter 5 was to identify attitudinal drivers of German crop farmers to use spot spraying on their own farm. Because this approach goes beyond commonly assessed sociodemographic and economic farm variables, it contributes to drawing a more holistic picture of likely important determinants of uptake, and our findings are thus highly relevant for agricultural economists and politicians who want to design effectual SFT dissemination strategies.

In the next section of the introduction to this dissertation, an overview of each chapter is given including a more detailed outline of the respective motivation, analytical approach and the results (Chapter 1.2). This is followed by the discussion of how the results of each chapter contribute to the overarching objective of the dissertation (Chapter 1.3). Finally, after the discussion of overarching limitations of this work (Chapter 1.4), we close with the implications for policy (Chapter 1.5).

1.2 Synthesis of research

1.2.1 Matching technology to behavior and context: Insights from a global meta-analysis of adoption studies in agriculture

Scientist have long been keen on learning about determining factors of the uptake of more productive, environmentally conserving, less risky agricultural innovations with early studies dating back several decades (e.g., Bell, 1972; Ervin and Ervin, 1982; Feder, 1982; Fliegel and Kivlin, 1966; Griliches, 1957; Yapa and Mayfield, 1978). Paralleled by the evolving diversity of agricultural innovations, the body of quantitative observational literature has grown, which today accumulates to a vast amount of farm-level studies to assess the relation of a multitude of economic, demographic, and contextual variables with farmers' adoption behavior. It has become increasingly challenging to retain an overview of the abundant literature and to distill universal statements regarding the relevance of certain adoption determinants to eventually inform the design of policies for the promotion of innovation uptake. Scholars have therefore conducted meta-analyses with varying degrees of methodological rigor and geographic and innovation-specific foci. The majority of these synoptic studies, however, could not come to unambiguous conclusions, suggesting that adoption might be highly specific to innovations and contexts "in which case inconsistency of results would reflect reality" (de Oca Munguia and Llewellyn, 2020, p. 88). Furthermore, readily observable economic farm characteristics and farmers' sociodemographic variables were operationalized disproportionately often, while more subtle variables depicting, e.g., farmers' attitudes, norms, or their embeddedness within their professional environment, remain relatively underrepresented (e.g., Thompson et al., 2023). In a similar fashion, specific characteristics of the innovations themselves as potential drivers of adoption were found to be largely absent from adoption research (de Oca Munguia and Llewellyn, 2020). In light of this equivocal evidence base, designing targeted and efficient innovation dissemination policies is a daunting task.

To get a comprehensive overview of the research landscape, Chapter 2 presents an up-to-date evidence map (Pullin et al., 2022) based on a global data set of published adoption literature. It focuses on multiple crop farming innovations, including new management or practice regimes, improved agricultural inputs, and technological innovations. This not only allows for the investigation of the frequency and statistical relevance of recorded adoption determinants but, by relating the former to the latter, it also enables the identification of currently underrepresented determinant categories that seem to bear relevant, yet not fully exploited, statistical information value for adoption research. As such, rather than deriving specific policy recommendations, Chapter 2 aims to give an orientation for future adoption research.

Through a multi-stage literature identification, selection, and recording approach (Havránek et al., 2020), a sizable data base with minimum possible bias was established, comprising over 32,000 individual adoption determinant observations stemming from 534 unique case studies. We assigned each observation to one of three vote count categories, namely 1) negative and significant, 2) insignificant, and 3) positive and significant. Compared to methodologically more rigorous meta-regressions with high data quality requirements (e.g., Schulz and Börner, 2023), our procedure enabled us to exploit a larger extent of the data set and further propose two disaggregated analysis perspectives, as aggregation is frequently assumed to mask sample heterogeneity (Wauters and Mathijs, 2014). For the first disaggregation approach, we differentiated agricultural innovations by four attributes. Specifically, we conceptualized innovations to be either risk-reducing, environmental footprint-reducing, productivity-increasing, or cognition-enhancing. This disaggregation allowed us to identify systematic differences regarding the inclusion frequency and statistical relevance of the adoption determinants in our data base for each innovation type separately. In the second disaggregation, we compared the results from studies conducted in OECD (Organization for Economic Co-operation and Development) and BRICS (Brazil, Russia, India, China, South Africa) countries to studies from the developing country context.

In line with previous research, we found that the majority of determinants originated in the categories of farm-level and operator characteristics, with most of them positively yet not statistically significantly associated with adoption. In contrast, variables measuring farmer attitudes, behavior, and their embeddedness in their social and professional environment have received substantially less attention in the literature, although several were significant in most cases. While this finding remained robust across the analyses, both disaggregation approaches revealed a more refined interplay in which certain variables from less researched categories had a high proportion of significant cases for specific innovation types (attributes) and country contexts, respectively.

1.2.2 Adoption intentions of smart weeding technologies–A lab-in-the-field experiment with German crop farmers

SFT are assumed a technological leap toward more sustainable and productive ways of farming (Lindblom et al., 2017; Walter et al., 2017), but their adoption is far from reaching the societally desirable momentum (Mizik, 2022; Spykman et al., 2021). Next to the fact that early technology prototypes are not yet profitable in all production systems (Lowenberg-DeBoer et al., 2020), farmers have expressed further concerns pertaining to increasing technological complexity and novel SFT characteristics, e.g., autonomous modes of operation and the ability to collect, process, and utilize large amounts of plot-specific data in real time (Fleming et al., 2018; Jakku et al., 2019; Scholz et al., 2021). Chapter 3 is thus concerned with the determinants of farmers' intended adoption of smart weeding technologies (SWT), namely spot spraying and an autonomous weeding robot. It complements Chapter 2 since it not only lays the focus on specific, barely researched and adopted sustainable agricultural innovations but also enhances our knowledge regarding potential underlying adoption mechanisms by assessing selected behavioral determinants and the effect of hypothetical policy interventions in an experimental case study setting.

Against the backdrop of the above considerations, which are likely explained by low levels of diffusion and technical information regarding specific SWT, Chapter 3 is based on a hypothetical approach, specifically a framed lab-in-the-field experiment (Gneezy and Imas, 2017). Due to high experimental control on the one hand but a professional subject pool–in our case composed of active crop farmers–and a hypothetical setting to mimic their everyday decisions on the other hand, lab-in-the-field experiments strike a balance between external and internal validity. Furthermore, since the experimental conditions can be framed according to the research context, lab-in-the-field experiments are a cost-efficient option to observe farmers' response to hypothetical policies, assuming that SWT were already fully operational.

The core of the incentive-compatible and pre-registered experiment, conducted in early 2022, consisted of a two-period business simulation game. German crop farmers were asked to choose from three different weeding technologies to set up a weed management strategy for a fictitious crop farming business with 50 hectares of farm land. A broadcast application boom represented a conventional technology with relatively high profits but no positive environmental impact. Spot spraying and a weeding robot represented the SWT alternatives with lower profits but positive environmental impacts. The aim of the first game round was to explain participants' intention to use SWT by a set of sociodemographic control variables and three behavioral measures, which were hypothesized to interact with novel features inherent to the presented SWT. These behavioral measures were farmers' attitudes toward the environment, toward farming innovations in general, and toward the security and privacy of farming data. In the second round, the sample was randomized into a control and three treatment groups. While the former group received the same experimental conditions as in the first round, the latter received a subsidy, a green nudge, and the combination thereof, respectively.

All policy treatments were hypothesized to increase the number of hectares allocated to SWT.

The results of the first round reveal that farmers with a more positive attitude toward the environment and innovations in general were statistically significantly more willing to use spot spraying and a weeding robot in their pre-treatment weeding plan compared to farmers with lower scores in these behavioral determinants. However, to our surprise and in contrast to the current debate in research and in public (e.g., Gabriel and Gandorfer, 2020; Jakku et al., 2019), farmers' lack of trust in agricultural data collected by autonomous machinery played no role for SWT adoption intentions with statistical or economic relevance in our sample. The second round yielded no statistically significant effect of any policy scenarios on intended SWT adoption. However, all treatment effects had a positive association with higher SWT allocation shares in the sense of the hypotheses at economically and environmentally relevant magnitudes. We assume that an unexpected behavioral phenomenon among study participants may be one major reason for the absence of significant treatment effects. Specifically, in round two and despite not having received a policy treatment, the control group showed a similar positive change in farm-land allocated to SWT in the sense of the hypotheses compared to the treatment groups. Although this phenomenon, which we coin "round effect", may not necessarily be unique to our experiment, we are not aware of any specific mention in experimental agricultural economics.

1.2.3 Round effects in economic experiments–Insights from a business simulation game with agricultural students

Chapter 4 is motivated by the phenomenon of the round effect identified in Chapter 3. As outlined, from round one to round two in the business simulation game above, all four experimental groups exhibited similar technology allocation changes which rendered the policy interventions statistically indistinguishable from zero. With the objective to learn whether this round effect is a subject pool effect (Peth and Mußhoff, 2020) brought about by the specific farmer sample or whether round effects are a phenomenon inherent to multi-period business simulation games, in Chapter 4, we replicated the above-mentioned lab-in-the-field experiment with agricultural students in an adapted design. As such, Chapter 4 is a methodological complement to Chapter 3. Rather than deriving policy recommendations or investigating how agricultural students perceive SFT, the aim of this chapter was, first, to make future agricultural economic experiments with similar designs aware of round effects and their potential consequences for the development of agricultural policies. Second, based on the comparison of the results gathered from the farmer and the student sample, we critically reflect upon the adequacy of using students as substitutes to study farmers' behaviors and attitudes.

Our adapted experimental design is strongly based on the precursory study in Chapter 3. As before, survey participants–placed in the role a fictitious crop farmer–received the task to use an arbitrary combination of broadcast application, spot spraying, and a weeding robot in order to conduct weed management on 50 hectares of hypothetical farm-land for two rounds. The pre-treatment round determinants of interest of intended SWT adoption remained pro-environmental attitude, personal innovativeness and trust in the security and privacy of farming data. For simplicity and in line with the aim of this study to narrow the focus on round effects, in round two, we only tested the effect of the subsidy paid for each hectare on which a smart weeding technology was used as policy treatment.

The multivariate analysis results of the student sample exhibit marked difference compared to the farmer sample in Chapter 3. First, the pre-treatment round findings for several attitudinal measures in the student sample contradict earlier findings from the farmer sample with respect to their direction of effect, their significance, and their magnitude. Second, while the control group did not significantly change their technology allocation pattern in round two, the treated group exhibited a distinct reaction to the subsidy via higher (lower) allocations shares of spot spraying and the weeding robot (broadcast application). On the one hand, this implies a significant policy treatment effect in the student sample which we did not find in the farmer study. On the other hand, this clearly hints at the absence of a round effect in this present case. In sum, the findings of 4 contrast what was previously found in Chapter 3. This fuels the debate about both temporal effects and the choice of subject pools in agricultural policy evaluation experiments.

1.2.4 Behavioral factors driving farmers' intentions to adopt spot spraying for sustainable weed control

Chapter 5 is built on a similar motivation as Chapter 3. It empirically assesses the determinants of farmers' adoption intention of SFT, a promising generation of sustainable agricultural innovations whose environmental potential is still largely untapped due to an early stage of technological maturity and a majority of crop farmers who have proven to be reluctant to adopt them. However, Chapter 5 looks at intended adoption through a purely behavioral lens which, according to our findings in Chapter 2 and previous conclusions in, e.g., Dessart et al. (2019) or Thompson et al. (2023), require reinforced attention. Furthermore, a behavioral approach is assumed to unravel subtle, context-specific adoption dynamics that may not necessarily be explained by purely rational decision-making aimed at profit maximization (Musshoff and Hirschauer, 2014).

This chapter is based on the TPB (Ajzen, 1991), which we extend and adapt according to our particular empirical setting, i.e., German farmers' adoption of spot spraying on parts of their fields within the next five years for high-precision weed management with substantial herbicide savings. The theory in its original form aims to predict an individual's behavior by three focal constructs: the individual's attitude toward the action, subjective (social) influences or pressures to perform it, and the individual's belief of being in control and capable of performing it (Ajzen, 1991). The theory is highly adaptable, and numerous previous examples have shown that context-specific model extensions can more precisely describe the background and decision context of the surveyed individuals (Sok et al., 2021). We therefore follow the recommendation by Fishbein and Ajzen (2010) and add further theory-informed context-specific extensions to the conceptual model. Namely, we hypothesize that farmers' personal innovativeness, pro-environmental attitude, and moral norms act as dispositional antecedents of their attitude toward spot spraying and the eventual adoption intention. Due to the exploratory nature of our conceptual setup, we use partial least squares structural equation modeling for the data analysis which is recommended as a flexible approach and particularly suitable for theory development and informing policy (Hair et al., 2017).

Since Chapter 5 is the second component of the larger investigation of German farmers' intended SFT adoption presented in this dissertation, data collection took place at the same time as the framed lab-in-the-field experiment (Chapter 3). The baseline model analysis reveals that our data is well in line with theoretical model predictions according to (Ajzen, 1991), i.e., farmers' attitude, subjective norms, and perceived behavioral control explain intended spot spraying adoption with good approximate model fit. Besides proving the baseline model findings robust, the extended model also revealed additional insights. We found a medium-sized total effect of moral norms, which suggests that our survey participants, on average, perceive a moral duty to reduce the amounts of herbicides applied on their land, which translates into a higher willingness to adopt spot spraying to achieve this goal. Furthermore, we could show with statistical significance that farmers with higher personal innovativeness develop a more favorable attitude toward spot spraying, which translates into a higher willingness to adopt it. In turn, although high average scores of pro-environmental attitude were found in the sample, we found no clear effect thereof on farmers' attitude and adoption intention of spot spraying.

1.3 Contributions

This dissertation investigates the adoption determinants of agricultural innovations on the farm level. In line with this overarching trajectory, each of the Chapters 2 to 5 has an individual motivation and builds on a unique methodological and contextual approach with respect to the innovations and adoption determinants investigated. In the following, we outline and synthesize the contributions of each chapter.

The meta-analysis presented in Chapter 2 contributes to the overarching objective of this dissertation, as it gives an extensive overview of the published quantitative literature focusing on the adoption of crop farming innovations. We emphasize the frequency and statistical significance of variables which are commonly (and not so commonly) used to model adoption on farm level. The findings were derived from the largest currently available database, which allowed us to investigate the sample in both its entirety and according to potential innovation- and context-specific heterogeneity. We agree with the conclusions of previous studies, i.e., although mostly positively associated with adoption, the vast majority of recorded adoption determinants were statistically insignificant in primary studies. This limits the scope to formulate immediate policy recommendations. However, we identified several adoption determinants that have a relatively low inclusion frequency in our sample but, when included, the majority thereof were statistically significant. This suggests a high explanatory value of these particular variables for innovation uptake. Since this promising finding does not allow for generalizability due to a small number of respective observations, these variable categories render themselves relevant candidates for future research. To this end, one major finding, namely the limited yet promising evidence for the impact of behavioral determinants on the adoption of eco-friendly innovations, further motivates Chapter 3 and Chapter 5 in this dissertation. Clearly, our comprehensive database is far from being fully exploited and may thus be of use for and extended by future research projects.

The first contribution of Chapter 3 to the overall objective of this dissertation lies in the fact that we conceptualize and relate behavioral determinants to anticipated novel attributes inherent to SFT. In other words, we investigate the association of a set of farmers' attitudes with their willingness to try out potentially eco-friendly innovations, although this may not be optimal from the perspective of a rational, economically thinking decision maker. We could show that, while more innovative and environmentally caring farmers express a higher intention to adopt spot spraying and autonomous weeding robots, their intentions are unaffected by concerns revolving around farming data. While this confirms the relevance of certain farmers' attitudes for SFT uptake, it also enables a more precise characterization of potential early adopters and the derivation of policy-targeting criteria. The second contribution lies in the evaluation of a set of plausible policy scenarios to promote sustainable smart weeding innovations. Although the policy treatments were not statistically significant, all estimates were positively associated with higher levels of adoption at relevant scales within the German agricultural context. This suggests that enhanced policy interventions may play a role in the future as SFT continue to mature. In sum, the findings of Chapter 3 are highly relevant for political stakeholders in addition to behavioral and agricultural economists who want to facilitate and accelerate sustainable intensification of modern agriculture based on experimental approaches. In identifying what we call a round effect, we further bring the attention of researchers to a methodological issue which, if unaccounted for, may cause the systematic misinterpretation of the results of multi-period experimental studies (cf. Thomas et al., 2019) and may potentially lead to ineffectual and costly policies.

The results in Chapter 4 yield no evidence of a round effect. We can thus assume that the round effect might be a phenomenon specific to the farmer sample collected for the study in Chapter 3. The first contribution of this chapter thus lies in increasing the awareness for round effects in future research. We further want to urge agricultural economists to develop alternative research designs to investigate round effects in more depth and to find out whether they are a phenomenon which can generally be observed in farmer samples. Second, in showing substantial differences between the farmers and the students in our samples regarding the effects of the attitudinal constructs and their responsiveness to the subsidy, we emphasize that students may not be adequate substitutes for agricultural policy evaluation studies (Peth and Mußhoff, 2020). Although collecting farmer samples increases the cost and required effort to conduct experimental agricultural economics research in the short run (Harrison and List, 2004), we argue that it will deliver more accurate and realistic insights and thereby contribute to the design of cost-efficient policies in the long run. Hence, our findings are relevant for experimental agricultural economists and policy makers who interpret and implement findings from multi-period business simulation games and similar experimental approaches.

Chapter 5 is a purely behavioral economics contribution to the objective of this dissertation. It applies and extends a psychological theory which relies on a set of attitudinal variables to explain farmers' adoption intention of a smart farming innovation for enhanced weed management with high potential to mitigate negative environmental impacts. On the one hand, our theoretical extension may inform future behavioral research in the field of SFT adoption. Our findings emphasize the role of farmers' moral considerations and their openness to innovations as key factors to determine their attitude toward spot spraying and their willingness to adopt it. This helps to paint a more holistic picture of farmers' intrinsic predisposition toward societally highly beneficial agricultural innovations. On the other hand, the study may enlighten agricultural policy makers, since our results underline the importance of channels for farmers to collaborate, exchange know-how and experiences regarding the benefits of SFT, and acquire adequate access to technological and financial resources. Given the sociodemographic profile of our survey participants, which points toward younger and well-educated farmers, our findings are based on a convenience sample and our analysis may therefore suffer from a lack of external validity. Nevertheless, we are convinced that we have captured a cohort of especially innovative and morally driven farmers who are willing to venture into an unknown field of sustainable technologies even if this may be associated with cost of investment, learning, or even structural farming system adaptations (Rogers, 2003;

Suvanto et al., 2020).

1.4 Limitations and future research directions

Beyond specific limitations discussed within each chapter, inherent caveats of the presented research require highlighting.

First, while our chosen meta-analytic approach in Chapter 2 is advantageous to the extent that it provides an extensive and largely unbiased picture of global adoption literature, it is this broad perspective alongside coarse methodological resolution which restrict the options to apply our findings in policy. Agricultural innovation adoption is highly context-specific, possibly even farm-specific. Clearly, policies need to consider and be adapted to such contextual factors to provide effectual solutions to promote uptake and diffusion of sustainable innovations. In spite of performing two disaggregated analyses, our meta-analysis summarizes research across socioeconomic and geographic contexts. This implies that even if our findings were more conclusive, designing agricultural policies to address adoption drivers and barriers of eco-friendly innovations would be a challenging task, as this would be based on findings spanning national or even continental borders. However, considering the size of our data base, the effort invested into establishing it, and the fact that we only analyzed a subset thereof, we want to encourage future research to build on and expand it to exploit its full potential.

Second, the novelty and low commercial availability of SWT limited our ability to capture their economic and environmental characteristics and accurately compare them to conventional broadcast application technology in the framed lab-in-the-field experiments in Chapter 3 and Chapter 4. As smart and autonomous farming technologies mature, a more precise quantification of innovation attributes with potential relevance for the adoption decision (Shang et al., 2023) next to observing the actual adoption process and diffusion patterns, will be possible. Eventually, this will contribute to more realistic and feasible empirical research leading to highly applicable insights. In any case, our findings can inform modeling exercises to predict adoption decisions on individual farms (Kuehne et al., 2017) and the diffusion process on a regional scale (Shang et al., 2021) and thus serve as a starting point and orientation for future research.

Third and in complementing the previous point, we acknowledge that the findings of Chapters 3, 4 and 5 may be prone to a low degree of external validity. On the one hand, a relatively controlled experimental setting with narrow decision-making space left the participants no room for improvisation to capture their decisions and behavior as would have been possible in real-life conditions. On the other hand, the survey participants themselves constitute convenience samples. The farmers contacted for Chapter 3 and 5 do not represent the underlying farmer population since, considering the diversity of farming structures in Germany, establishing a representative farmer sample would have exceeded the resources of our project. By contrast, the students which we sampled for Chapter 4 may not have been an adequate subject pool to begin with in order to derive insights for the design of policies addressed to farmers. Nonetheless, as we argue in the respective chapters, our findings may methodologically inspire future research and may also be useful for policy makers, since it is younger, well-educated farmers, as found in our sample, with innovative and pro-environmental dispositions among which adoption of SFT is likely to gain momentum.

Fourth and last, framing and analyzing adoption through the lens of individual farmers as a one-time event may be a premature perspective which omits additional relevant considerations. In fact, adoption is a process which spans multiple stages, from becoming aware of, evaluating, trailing and finally adopting or even discarding an innovation (Kuehne et al., 2017; Ruzzante et al., 2021). Moreover, previous works suggest that the influence of farmers' proximate peers (Massfeller and Storm, 2023) and farming system dynamics on a regional level (Shang et al., 2021) define the adoption and diffusion patterns. All these are vital aspects which future works need to incorporate to holistically study this topic.

1.5 Policy implications

The adoption of innovative management processes and technologies is seen as a major building block of steering agricultural production systems globally toward more sustainable and economically more viable outcomes (Springmann et al., 2018). Due to societally suboptimal rates of adoption and diffusion, these expected benefits remain far from being exploited, and our attempt to distill generalized adoption determinants from the vast amount of adoption research in Chapter 2 has resulted in few conclusive findings.

If anything, the presented work shows that adoption is highly specific to the innovation type and context under investigation. As further demonstrated in Chapter 3 and Chapter 5, adoption is co-determined by behavioral and innovation-specific aspects, which scientists have only recently become aware of. Policy designs to promote sustainable innovations in general and SFT in particular should consider these contextual aspects and provide a variety of aligned strategies instead of a one-size-fits-all approach to achieve the desired momentum. In the following, we discuss a non-exhaustive list of policy recommendations with different scopes and, where possible, we draw on selected participants' verbal responses recorded in the course of our empirical study with farmers to accentuate our elaborations.

The numerical results of Chapters 3 and 5 indicate, on average, a positive intention to use SFT among the sampled farmers. The fact that our convenience sample may already represent a relatively innovative cohort of farmers and seeing that the majority of farmers retain a large share of conventional weeding methods in their technology mix (Figure 3.2) suggests that we have probably overestimated the SFT adoption intention of the underlying German farmer population. However, finding high average moral and pro-environmental dispositions in our sample (Chapter 5) may hint at the effectiveness of technology demonstrations and informational or nudging campaigns, which emphasize the environmental benefits and functionality of SFT and specifically appeal to farmers' perceived environmental responsibility (Dessart et al., 2019; Thomas et al., 2019). Along these lines, one farmer expressed the following:

"Spot spraying should come along with demonstrations, recommendations and financial support. I haven't dealt with it yet since it appears to be too expensive and impractical."

Especially in the early stages of technological development, substantial incentives might be needed to overcome the reluctance of potential early adopters and to accelerate diffusion. Although we show in Chapter 3 that a partial compensation of the opportunity cost incurred by switching from a conventional technology to a sustainable SFT can already have a positive impact on farmers' SFT adoption intention, higher financial support to remunerate farmers for their contribution to a healthy environment may send a stronger signal and create a feeling of public appreciation. The following quotes from survey participants underline this:

"As long as politicians and society don't reward environmentally conducive actions appropriately, I see no bright future for our local agriculture."

"Societal utility needs to be rewarded via monetary compensation or governmental support for farming business expansions."

Both our findings in Chapter 5 and previous literature highlight the importance of communication and collaboration channels. Including farmers into the design of regional policy frameworks (Westerink et al., 2017) and providing payments based on participation in collective agri-environmental schemes can increase collaboration (Kuhfuss et al., 2016; van Dijk et al., 2015). It can further motivate collective investment in and sharing of agricultural innovations among adjacent farmers to overcome financial bottlenecks and promote the accumulation and exchange of expertise (Blasch et al., 2022). Additionally, subsidies which are made conditional upon a minimum number of participating farmers in a given region may benefit the uptake of SFT due to their normative effect (Kuhfuss et al., 2016). This may contribute to building a social identity and promote the dissemination of group norms which are known to develop in an environment of like-minded peers (Terry et al., 1999) and which have been shown to determine the intention of sustainable innovations uptake (Bonke and Musshoff, 2020).

A related line of thought pertains to the design of research conducted within the agricultural knowledge and innovation systems. Since several farmers left a comment regarding valid potential improvements of our empirical design (not shown here), we recommend reinforcing the inclusion of knowledgeable and innovative farmers into future research networks to increase collaboration and learning among interdisciplinary actor groups, e.g., scientists, farmers, and politicians (Hermans et al., 2015). This will not only enable the design of effective policies to promote pathways toward more sustainable agriculture, but it will inform agricultural technology producers to tailor innovations to the specific needs of practitioners.

On another note, with increasing degrees of digitalization of agriculture, the role of a farm operator, as we currently conceptualize it, is likely to undergo substantial alterations, which will require us to rethink farming from several perspectives. Current examples of SFT draw on rapidly recorded and analyzed data to enhance decision-making and the precision of individual process steps but, importantly, the primary decision-making power remains with the farmers. However, as agricultural machinery becomes increasingly autonomous, intelligent, and safe, a plausible scenario takes shape in which agricultural robots independently plan and execute manual routine tasks, e.g., harvesting or the application of pesticides (Marinoudi et al., 2019). On the one hand, this will change the job profile of future farmers, who will have to expand their knowledge and skills in fields of digital literacy and engineering to operate and maintain novel technologies. On the other hand, a continuous substitution of human workers by agricultural robots will exert additional pressure on agriculture as an economic sector, especially, in countries with a high share of traditional, small-scale agricultural structures (Marinoudi et al., 2019). To enable farmers to stay up to date and partake in these anticipated developments, policy frameworks aimed at financial support and education are urgently required.

Finally, although not supported by our analysis in Chapter 3, unresolved questions revolving around big data and AI in agriculture continue to give rise to ambiguous debates in the public and scientific sphere (Finger, 2023; Jakku et al., 2019; Scholz et al., 2021; Sparrow and Howard, 2021; Wolfert et al., 2017). Future research and technological developments next to the implementation of SFT should thus be aligned with and embedded in comprehensive legislative and ethically sound action plans. This will preserve farmers' bargaining power vis-à-vis international technology producers and food companies, and it will limit the threat of exacerbated market concentration.

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Chapter 2

Matching technology to behavior and context–Insights from a global meta-analysis of adoption studies in agriculture

Abstract: An abundant body of case studies and meta-analyses on the uptake of eco-friendly, more productive, and efficient agricultural innovations across diverse farming contexts and research methodologies has been published in recent decades. In light of global socioeconomic, climate, and environmental challenges, it is of high public and scholarly interest to learn about the underlying mechanisms of adoption and diffusion of agricultural innovations to incentivize and accelerate these processes to make agricultural production more sustainable at relevant scales. However, it has proven difficult to unambiguously determine which general factors are important drivers of adoption. We establish the largest currently available global data set based on published ex-post adoption literature to provide an updated evidence map of frequently and less frequently studied adoption determinants. Next to the aggregate analysis, we delve deeper into potential sample heterogeneity by disaggregating the data according to socioeconomic contexts and innovation attributes–a newly developed concept to characterize and study the relative advantage of innovations. Our findings are by and large in line with previous review studies. However, we highlight relatively understudied yet statistically promising behavioral and diffusion factors for future scientific exploration. Moreover, we find indications of behavioral determinant-innovation attribute pairs, suggesting that the role of the interaction of intrinsic farmer and innovation characteristics to explain specific adoption dynamics should be exploited in future studies. Our work is thus primarily aimed at informing and helping refine future adoption research.

Keywords: Adoption determinants, agricultural innovations, global evidence map, innovation attributes, context, relative advantage

JEL classification: Q16, Q18, O13, O33

2.1 Introduction

Intensive agricultural production is associated with a host of adverse environmental impacts such as, inter alia, land use changes, greenhouse gas emissions, deterioration of ecosystems in water and on land, and declining biodiversity (Newbold et al., 2015; Springmann et al., 2018). Accentuated by the increasing global food demand trend (Tilman et al., 2011), it thus appears paramount to intensify global food production in a sustainable manner (Garnett et al., 2013) to continue to provide enough healthy food while staying within the planetary boundaries (Springmann et al., 2018; von Braun et al., 2021). In this endeavor, a plethora of agricultural innovations have been developed and adopted around the world.

In a broad sense, innovation is described as a continuous process during which businesses ameliorate their competitiveness and relative market position by developing and implementing improved processes, services, or products (Baregheh et al., 2009). For the purpose of the present study and in line with, e.g., Nord and Tucker (1987) and Rogers (2003), we, however, apply a narrower definition and henceforth depict agricultural innovations as novel technologies and improvements of in-field or on-farm practices with the purpose of enhancing the economic and/or environmental performance of an individual farming operation (Schulz and Börner, 2023). As such, agricultural innovations range from new inputs, e.g., high-yielding or resilient seed varieties, fertilizers or pesticides, to adapted management processes or growing regimes, e.g., agroforestry or intensified crop rotations, to digital technologies, e.g., mobile farming apps for decision support, drones for aerial pest scouting, or fully autonomous field robots for precision application of agrochemicals and mechanical weed management.

In light of their presumed environmental and economic potential, research on the uptake of agricultural innovations to inform stakeholders in policy, industry, science and non-governmental agencies has a long-standing history, which has resulted in a rich body of literature for a wide range of innovations and contexts. Similarly, to aggregate and organize overarching conclusions, a number of literature reviews and meta-studies have been conducted, looking at different innovation types next to varying contextual foci and resolutions. However, despite profound research efforts, no universally valid conclusions could be drawn.

The present meta-analysis is based on a unique and, to the best of our knowledge, the largest available global data set of agricultural innovation adoption literature. It is composed of systematically acquired and rigorously coded quantitative ex-post analyses investigating the adoption determinants of a multitude of eco-friendly innovations in crop productions systems. We comprehensively take stock of the published literature by assessing the relative occurrence frequency and the statistical significance of commonly used adoption determinants. Next to the analysis of the full data set, two disaggregated perspectives are presented to refine the understanding of circumstances under which certain variables may become statistically relevant and unambiguous in their direction of impact on adoption. Furthermore, we identify determinant categories which, despite their relevance according to our analysis, have received comparatively little attention. Rather than deriving explicit policy recommendations, the primary aim of our work is thus to inform future research and shed further light on currently underrepresented yet informative and potentially context-specific drivers of agricultural innovation adoption.

Due to the diversity of published reviews of innovation adoption literature, it has proven difficult to find overarching agreement for multiple reasons, a prominent one being the difference in geographical contexts. Several reviews established data sets on the global level (Lopez-Avila et al., 2017; Pierpaoli et al., 2013; Rajendran et al., 2016), while others focus on developed (Baumgart-Getz et al., 2012; Dessart et al., 2019; Tey and Brindal, 2012) or developing countries (Jack, 2013; Macours, 2019). Furthermore, several articles have restricted their scope to specific categories of innovations not readily comparable such as precision farming technologies (Pathak et al., 2019; Shang et al., 2021; Tey and Brindal, 2012), soil conservation (Wauters and Mathijs, 2014), eco-friendly innovations for fertilization (Hasler et al., 2017), or organic farming (Lamine and Bellon, 2009). This is contrasted by articles that incorporate multiple innovations at once under the umbrella of sustainable, conservation, or best management practices (Baumgart-Getz et al., 2012; Knowler and Bradshaw, 2007; Liu et al., 2018; Prokopy et al., 2019). Additionally, review studies differ in their objectives and respective methodologies. Several meta-regressions determine effect size ranges of selected determinants of uptake (Baumgart-Getz et al., 2012; Rubas, 2004; Ruzzante et al., 2021; Schulz and Börner, 2023), while other articles investigate adoption through a conceptual and theoretical lens (de Oca Munguia et al., 2021; Gallardo and Sauer, 2018). However, we predominantly find studies based on vote count analyses (de Oca Munguia and Llewellyn, 2020; Knowler and Bradshaw, 2007; Prokopy et al., 2019; Schaub et al., 2023), qualitative and narrative reviews (Dessart et al., 2019; Macours, 2019), and evidence maps (Lopez-Avila et al., 2017; Thompson et al., 2023). Lastly, while several reviews used a systematic literature search approach (Pathak et al., 2019; Schaub et al., 2023; Schulz and Börner, 2023; Shang et al., 2021), non-systematic approaches are disproportionally represented (Baumgart-Getz et al., 2012; Dessart et al., 2019; Knowler and Bradshaw, 2007; Ruzzante et al., 2021).

This overview is not meant to be exhaustive; however, it gives an approximate notion of the diversity of review literature and further illustrates that each approach, intentionally or unintentionally, introduces bias.[2] This may be one major reason why a large share of the above literature syntheses did not yield clear findings regarding the significance and impact of direction of assessed adoption variables. In addition, the majority of variables used in primary case studies originated from the categories of farmer and farm characteristics while the importance to investigate behavioral determinants (Dessart et al., 2019; Schaub et al., 2023) and to emphasize characteristics depicting the technology to be adopted (de Oca Munguia and Llewellyn, 2020) has only recently been recognized.

Clearly, this challenges researchers, politicians, extension service providers, and non-governmental stakeholders alike because the derivation of unambiguous recommendations for research and policy agendas next to innovative business plans is not straight-forward. Against this backdrop, we do not conduct yet another literature review with a preset geographic and innovation-specific focus. In building on Thompson et al. (2023), our aim is rather to identify and organize the published quantitative adoption literature to provide an updated evidence map (Pullin et al., 2022). In applying a systematic literature search and screening approach, which includes both statistically

[2] We acknowledge that there may be additional types of bias at the primary case study level, introduced by limitations in the conceptualization of the adoption mechanisms and respective estimation procedures. A discussion thereof would exceed the scope of this chapter. Nevertheless, a review of potential sources of bias at the case study level can be found in Ruzzante et al. (2021).

significant and insignificant findings, we keep potential bias of, e.g., selection or confirmation, to a minimum (Aromataris and Pearson, 2014; Schaub et al., 2023). Specifically, we investigate the frequency of common (and less common) independent variables in primary adoption studies. Furthermore, we test whether these variables are, on average, consistent regarding their significance and direction of impact on adoption. Lastly, we relate the frequency of included determinants to their statistical consistency, which enables us to derive cautious statements regarding the relevance which certain variables bear for those adoption studies in our sample. Although our insights may enable the formulation of policy recommendations, our primary aim is to identify knowledge gaps and thereby inform future research (Pullin et al., 2022).

Our global perspective across multiple technological and managerial innovations allowed us to identify a vast amount of literature, which required random selection of potentially eligible articles to keep the manual coding effort to a manageable amount. Our data base is thus considered a convenience sample. This notwithstanding, the large size of our data set allowed us to refine the analysis by two disaggregation approaches to investigate potential heterogeneity in the data. First, we looked for systematic differences in adoption determinants when the innovations were investigated separately according to their attributes. Specifically, we developed and applied a theory-informed concept which assumes that innovations bear a set of attributes, i.e., characteristics, that are conducive to the economic or and/or environmental outcome of the farming business, which thereby makes them relatively advantageous compared to the status quo of technology or practice. Second, we conducted a context-specific analysis, i.e., we looked for diverging patterns in adoption determinants when OECD (Organization for Economic Co-operation and Development) and BRICS (Brazil, Russia, India, China, South Africa) country findings were compared to studies conducted in developing countries.

Our contributions are thus threefold. First, our sizable systematic data base allows us to give an updated overview of published research on the uptake of agricultural innovations for a broad spectrum of crop farming innovations in a multitude of countries. Second, running disaggregated analyses enables us to learn under which circumstances certain variables may play a pronounced role. Lastly, we identify variables which have thus far been of low scholarly interest but which bear relevant statistical potential for future research.

Following this Introduction, Section 2.2 presents the concept of innovation attributes used as part of the disaggregated analysis. This is followed by Section 2.3, in which the systematic literature and data acquisition and recording process is detailed. In Section 2.4, we present the results of the aggregated and disaggregated analyses, followed by Section 2.5, in which we summarize and discuss the results, critically reflect upon this study, give an outlook for future research, and provide a conclusion.

2.2 Innovation attributes

The synoptic literature agrees that the majority of research on the uptake of agricultural innovations primarily assessed the role of readily observable farmer and farm characteristics. Aspects of the studied innovations, however, have not systematically been taken into account (de Oca Munguia and Llewellyn, 2020). Yet, when considering the spectrum of technology and process attributes, i.e., characteristics, one may intuitively expect to find interactions among certain innovation type-adoption determinant combinations. In this section, we present a concept to group innovations by their attributes for one of the subsequent disaggregation analyses. Thereby, we contribute an alternative approach to previous investigations which set out to find systematic patterns in the relevance of adoption determinants when innovation types are considered separately (Arslan et al., 2022; de Oca Munguia and Llewellyn, 2020; Schulz and Börner, 2023).

Our approach was motivated by Rogers' (2003) seminal work on the diffusions of innovations, which has a focus on the attributes of the innovation. Specifically, we built on the claim that an innovation will be adopted and diffused given that it is relatively advantageous compared to the status quo of technology or practice.[3] We conceptualized the relative advantage to capture focal areas frequently stressed in the ongoing debate on sustainable intensification of global food systems (Section 2.1).

Theory predicts that profitability may serve as the prime reason for innovation uptake (Rogers, 2003). Accordingly, innovations are said to be relatively advantageous when they are in line with a supposedly rationally acting farmer's objective to maximize profit or minimize the expected losses (Khanna, 2021; Khanna et al., 2022; Tey and Brindal, 2012). However, whether an innovation is truly profitability-increasing primarily

[3]See Rogers (2003) for a detailed depiction of further innovation attributes, stylized stages of the adoption process, and a characterization of types of adopters.

depends on a farm's individual return and cost structures and other contextual factors, and can thus not be assumed under all circumstances (Khanna, 2021; Lowenberg-DeBoer et al., 2020). Second, several subordinate aspects simultaneously determine profitability and require separate consideration. Lastly, farmers may value additional integral innovation characteristics which are not necessarily related to economic performance but pertain to practitioners' attitudinal and psychological dispositions (Dessart et al., 2019; Kuehne et al., 2017). As such, an innovation reveals its potential through several impact pathways (Khanna, 2021) and is thus viewed as relatively advantageous when it helps to pursue any of a farmer's, oftentimes interdependent, objectives (Khanna et al., 2022; Thompson et al., 2019). We now elaborate on four specific attributes to describe the relative advantage of innovations in more detail.

A frequent observation is that innovations boost productivity, i.e., they improve the ratio of output to input. This is achieved by increasing production quantity while the input quantity is held constant, by reducing the required inputs while production quantity is held constant, or by simultaneous changes in both output and input quantities (Finger et al., 2019; Khanna, 2021; Khanna et al., 2022; Macours, 2019; Sunding and Zilberman, 2001; Thompson et al., 2019). For example, an output increase is achieved by augmented yields through the application of fertilizers and higher-yielding seed varieties, or the reduction of yield losses via the usage of plant protection measures or improved weed management. In turn, input reductions are achieved by, e.g., improved seed varieties which require less nutrients, mechanization of managerial processes which reduces manual labor requirements, or precision input application adapted to the heterogeneity of the field.

The term productivity conceptually overlaps with the notion of input-use efficiency. However, while improvements in the former are primarily associated with economic benefits, improvements in the latter address environmental benefits. Evidently, innovations which improve the input–output ratio not only benefit a farmers' budget but may also achieve a more efficient use of resources and inputs, thereby reducing adverse environmental impacts per unit of agricultural produce (Finger et al., 2019; Khanna, 2021; Khanna et al., 2022; Li et al., 2018; Thompson et al., 2019). Furthermore, the anticipated environmental advantages of more efficient innovations may incentivize their adoption independently of economic benefits, as detailed in Kuehne et al. (2017). This seems to be particularly relevant for farmers with a high pro-environmental attitude and intrinsic or perceived moral obligation to reduce the negative environmental impacts of their farming practices as suggested by Dessart et al. (2019), Feisthauer et al. (2024a), and Feisthauer et al. (2024b). Specific environmental benefits result from lower application and improved resorption of inputs (e.g., pesticides, fertilizer, water) due to precision application and improved seed varieties, respectively, which can reduce runoffs and the associated deterioration of ground-water and soil. Furthermore, negative environmental impacts can be mitigated by reducing the intervention intensity aiming to conserve agricultural land via, e.g., cover crops, conservation tillage regimes, or more systematic innovations such as agroforestry, refined crop rotations, or integrated pest management.

Another aspect is primarily introduced by digital and smart farming technologies that assist and enhance cognitive and managerial processes by enabling more informed decisions making next to more adequate and accurate execution of farming practices across heterogenous space and time (Finger, 2023; Tey and Brindal, 2012; Wolfert et al., 2017). This is facilitated by rapid collection of high-resolution data via smart cameras and sensors, computer-based aggregation and interpretation of large amounts of data from different sources to provide managerial recommendations, and site-specific execution of management tasks, e.g., harvesting, chemical application, or weed removal adapted to the soil variability within a plot and to the requirements of individual plants (Marinoudi et al., 2019; Walter et al., 2017; Wolfert et al., 2017; **?**). While overlaps with the previous positive impacts on productivity and the environment are apparent, we emphasize here the enhancement effect on practitioners' cognitive capacities and skills that they would otherwise not be able to have.

Lastly, agricultural innovations can lower the production risk and reduce yield variability due to more stable and secure harvests (Kuehne et al., 2017; Lowenberg-DeBoer, 1999; Tey and Brindal, 2012). Several previously discussed innovation features, especially those of digital farming technologies, are linked to the risk-reducing characteristic as they help to anticipate and adapt to environmental factors and uncertainty revolving around heterogenous soil and growing conditions (Khanna, 2021). Additionally, innovative management approaches and practices, e.g., cover crops or agroforestry, can reduce the risk of water and wind erosion while modernized plant protection measures can mitigate the risk of pest infestations.

In sum, we state that the relative advantage of innovations manifests in their risk-reducing, environmental footprint-reducing, productivity-increasing, and cognition-enhancing attributes. Clearly, the attributes are neither exhaustive nor mutually exclusive, i.e., one innovation may be characterized by more than one attribute since they interact by construction (Khanna et al., 2022) (see details in Table A4 and Text A5 in the Supplementary Information). Nevertheless, it represents a first heuristic approach that allows us to comply with demands by Pannell et al. (2006) and Kuehne et al. (2017), who stressed the need both to emphasize the role-specific characteristics inherent to types of innovations and to shed light on their interaction with commonly recorded adoption determinants. This may reveal heterogeneity in adoption dynamics caused by context specificity and may further help to understand barriers and drivers of uptake and diffusion. We explain in Section 2.3.3 the implementation of attributes into our analysis.

2.3 Materials and methods

2.3.1 Identification of primary literature

We followed a systematic literature search and multi-stage screening protocol (Havránek et al., 2020) in the field of agricultural innovation adoption (Figure 2.1). In a first step, 1,423 eligible references were gathered from priorly identified review papers in this field. Second, a text mining approach (Grames et al., 2019) applied to the identified publications enabled the construction of a systematic search string, which was then applied to the databases Web of Science, AgEcon Search and EBSCOhost. The literature query took place on May 6th, 2020, and amounted to 27,043 peer-reviewed publications. With the help of an automation technique, titles and abstracts of identified records were evaluated and ranked according to their potential eligibility, leaving 6,983 studies for manual screening. Next, we adopted and applied on the study level a set of PICOS eligibility criteria commonly used in systematic clinical literature search (Tacconelli, 2010). Accordingly, only publications with crop farmers as the target population (P) excluding livestock and horticulture, agricultural practice and technology adoption as focal intervention (I), studying adopters in comparison to the control group of non-adopters (C), and farm-level adoption as the outcome (O) were selected, while all ex-ante measures (e.g., intention or willingness to adopt) were dropped. Furthermore, only studies with quantitative causal analyses (S) were included, while all qualitative and non-causal quantitative study designs were left out. Subsequently, a randomly selected sample of 534 eligible primary publications was rigorously recorded (meta data and analysis-specific model coefficients) in a spreadsheet. Therefore, the final data set needs to be regarded as a convenience sample. Due to the applied literature search strategy, eligibility assessment, and coding approach, it is possible that not all eligible studies were identified. However, similar to Schulz and Börner (2023), we state that non-identified studies do not systematically differ from identified ones.

The data base was designed to contain the estimated model coefficients of adoption determinants (x-variables) extracted from primary case studies, next to the descriptive statistics, i.e., the means and standard deviations of independent variables, model specifications, description of the technology or practice under assessment, the scale and measurement thereof, and characteristics and size of the collected farmer sample. The coding process revealed a multitude of both independent and dependent variables. To facilitate later analyses and interpretation, the categorization framework in Prokopy et al. (2019) was extended, and a total of 45 and 20 categories for independent and dependent variables, respectively, were formed. The final data base contained a total of 32,079 observations from 534 unique studies. More details on the literature identification strategy can be found in Texts A1 to A5, Tables A1 to A5, and Figures A1 and A2 in the Supplementary Information.

2.3.2 Data set

After having established this comprehensive data base, further filtering steps were performed (Figure 2.1). First, applying the adapted set of PICOS criteria on the observation level further reduced the number of observations to 17,814. Second, after removing duplicates (n=78), only observations for which a p-value, t-statistic, or standard error could be extracted from primary studies were retained (n=15,940). Based on these recorded measures of estimation precision, we derived the significance of the recorded effect estimates by comparing them against a general 10% significance level (Borges et al., 2019; Shang et al., 2021) (see Text A6 in the Supplementary Information for details). To enable the unambiguous interpretation of impact direction of the adoption determinants as defined in Table A3, we coded them in a way such that positive estimates were generally associated with higher likelihood or levels of adoption. In several cases, however, we had to rely on unstandardized model coefficients, e.g., odds ratios in logit models, and analyses with an unintuitive definition of the outcome variable, e.g., survival analyses. This required careful interpretation and potentially a recoding of the outcome variable or determinant. Having established significance and direction, all recorded coefficients were thereafter assigned one of three vote count classes, namely negative significant, insignificant, and positive significant in the sense of our definition of adoption. Third, all adoption determinant categories which had no intuitive or meaningful interpretation of direction (geography, other, interaction terms) were dropped, yielding the final sample of 13,748 observations extracted from 383 unique primary studies. As a quality criterion, we additionally ascertained that observations for each individual variable category were collected from at least five different studies. In a last step, the attributes (Section 2.2) were assigned to all innovation categories. For this task, a binary coding scheme was developed and applied to the innovation categories by four members of the research group in a blinded manner. In this process, a final inter-coder agreement of 89.5% could be reached. A detailed description thereof can be found in the Supplementary Information in Text A5, the final data set is available on OSF.

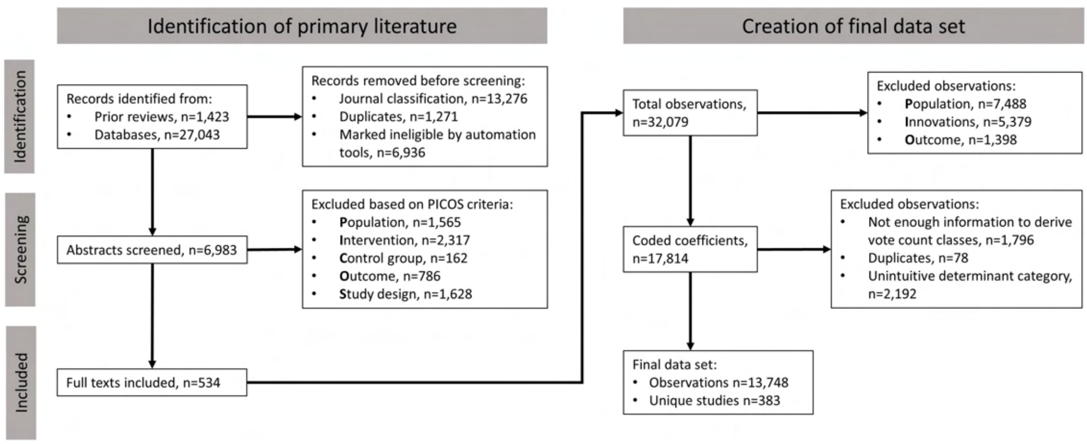

Figure 2.1: PRISMA diagram of identification of primray literature and creation of the final data set.

2.3.3 Analysis

Arguably, formal meta-regressions which are concerned with the assessment of the magnitude and precision of effect sizes allow for the most in-depth investigation of adoption determinants (Schulz and Börner, 2023). However, meta-regression is conditional on the comparability of effect sizes across primary studies, which further necessitates the availability of standardized coefficients (Shang et al., 2021). Standardization of coefficients can, in principle, be performed for each adoption determinant; however, this would require further measures of precision, i.e., standard deviations of both dependent and independent variables of primary studies, which are not reported in all cases. Limiting the scope of the analysis to studies with sufficient information would have drastically reduced the size of the present sample. In line with the objective of this study, we therefore opted for a vote count procedure to exploit a larger extent of the database and maintain a broader, less selective perspective on the published evidence on adoption.

We investigated the sample from different perspectives. First, we performed a descriptive analysis of the geographical distribution of the data with respect to research intensity and diversity, i.e., the number of eligible studies and innovations identified. Similar to previous reviews (e.g., Knowler and Bradshaw, 2007; Prokopy et al., 2019), we then performed a vote count analysis to take stock of the frequencies of included adoption determinants across primary studies and compared the number of insignificant, significant positive and significant negative cases to each other. We further related the frequency in which individual variables were included in eligible studies to the frequency of being found significant to determine their relative explanatory value in the identified adoption research (Thompson et al., 2023). Furthermore, we followed de Oca Munguia and Llewellyn (2020) and conducted two-proportion z-tests to ascertain the consistency of the direction and significance for each variable with the aim to formulate statements about their (statistical) relevance in adoption research. Lastly, as proposed by Wauters and Mathijs (2014), we addressed potential sample heterogeneity and repeated the analysis with two different disaggregation approaches, namely we disaggregated by innovation attributes as described in Section 2.2 and by geographical context, i.e., OECD and BRICS versus developing countries.

2.4 Results

2.4.1 Descriptive analysis

The primary studies containing the adoption determinants for our data set assessed the uptake of multiple innovations across a range of countries (Figure 2.2). Since we incorporated parts of the data set in Floress et al. (2019), our sample is biased toward studies conducted in the United States. Furthermore, with respect to the number of studies and diversity of innovations, several sub-Saharan countries (Ethiopia, Nigeria) and Asian countries (China, India, Bangladesh) alongside Brazil and South Africa contribute a large share of adoption research to the data set while Latin American and European countries are underrepresented.

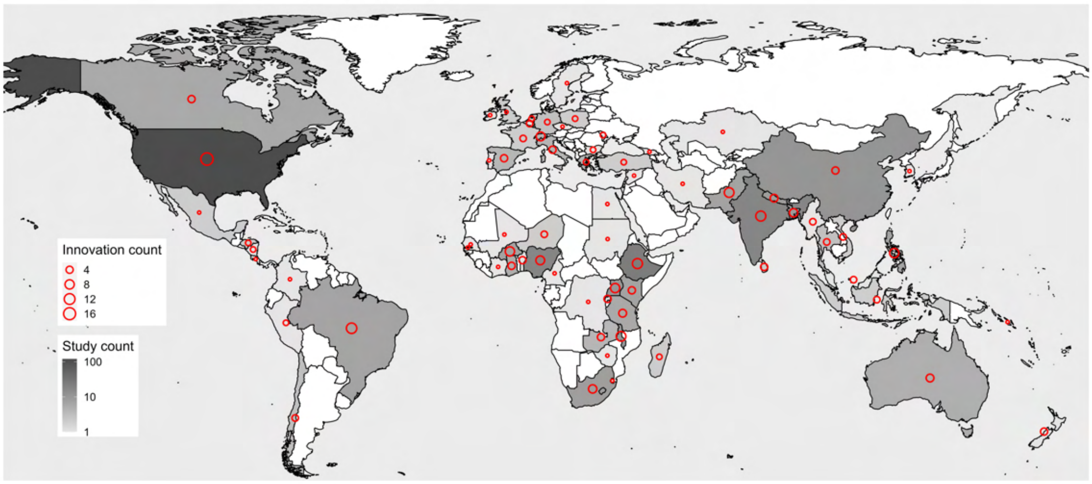

Figure 2.2: Global representation of number of identified studies and respective innovations.

Note: The shading color indicates the number of studies per country included in the data base. The size of the circles gives an orientation for the number of different innovations assessed per country in the included studies. For example, for Brazil 7 case studies were identified in which a total of 11 different innovations were investigated. The underlying data can be found in Table A6 in the Supplementary Information.

Furthermore, when comparing OECD and BRICS nations to developing nations, diverging research priorities regarding the types of innovations become apparent (Figure 2.3). While approximately 10% of all studies in our OECD and BRICS subsample assessed cognition-enhancing innovations, a negligible number of studies did so in developing nations. Moreover, the share of studies examining environmental footprint-reducing innovations in the OECD and BRICS data is about eight percentage points higher. By contrast, studies on risk-reducing and productivity-increasing innovations are more prominent in developing countries by a difference of approximately eight and ten percentage points, respectively.

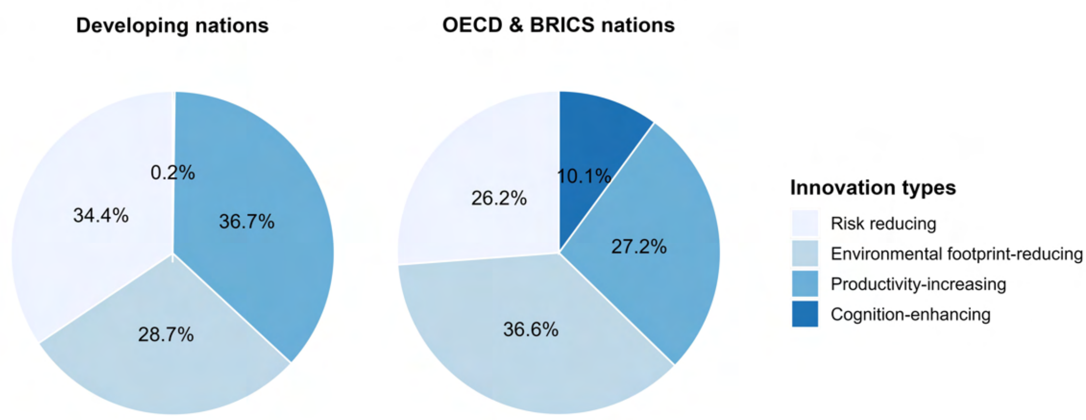

Figure 2.3: Adoption research by geographic contexts and innovation types.

Note: Percentages represent the share of studies assessing different innovation types in a given geographic context. For example, in developing nations, 34.4% of included publications studied risk-reducing innovations. Detailed counts of studies per individual innovation category and context are displayed in Figures A5 and A6 in the Supplementary Information.

2.4.2 Aggregated analysis

We now turn to the focal part of the analysis and assess independent variables used in primary studies as adoption determinants.[4] We relied on Shang et al. (2021) and Wauters and Mathijs (2014) to categorize all determinants into seven larger thematic groups (Table 2.1). Similar to recent reviews (e.g., Shang et al., 2021; Thompson et al., 2023), the most included and diverse variables in our data set are (economic) farm characteristics and sociodemographic variables, while biophysical factors, institutional factors, and innovation traits rank at the lower end of Table 2.1. In between rank diffusion factors, i.e., variables describing channels of information and resource acquisition, and farmer communication, followed by behavioral factors.

[4]Table A3 in the Supplementary Information contains the definitions of all adoption determinants identified.

Table 2.1: Count of observations by adoption determinant category, full data set (n=13,748).

Adoption determinant category	Sum	Adoption determinant subcategories
Farm characteristics	4,924	Farm size, labor, other practices, tenure, livestock, capital, specialization, market distance, diversity, asset value, dependency, irrigation, productive assets, yield
Sociodemographic factors	3,832	Formal education, age, income sources, income farm, experience, operator sex
Diffusion factors	1,969	Sought/use, network, assistance, affiliation, evaluation, marketing
Behavioral factors	1,039	Environmental attitude, innovativeness, farmer identity, risk
Biophysical factors	760	Vulnerable, soil quality, weather
Institutional factors	621	Subsidy, input cost, agricultural economy, institutional
Innovation traits	603	Innovation traits

Figure 2.4 depicts the frequency of adoption determinants in more detail, i.e., the observations for each variable partitioned into their vote count classes. The 15 most frequent variables stem from the groups of farm characteristics, sociodemographic factors, and diffusion factors except for the variable innovation traits (cf. Table 2.1). For most variables, the majority of recorded cases were insignificant with few exceptions, namely diversity, productive assets, weather, environmental attitude, innovativeness, input cost, and subsidy. Moreover, among the cases identified as significant for each variable, the majority had a positive association with adoption except for the variables age and risk.

In a next step, we investigated how frequently adoption determinants were used in the statistical models of primary studies relative to their information value, i.e., whether the variable inclusion frequency across all eligible models in the data set was matched by the frequency of being found statistically significant (cf. Thompson et al., 2023). In Figure 2.5, the former is given by the ratio of the number of occurrences of an adoption determinant to the total number of models (not studies) in the data set (x-axis). The latter is given by dividing the number of significant determinants extracted from the models by the total number of occurrences of the respective determinant (y-axis).

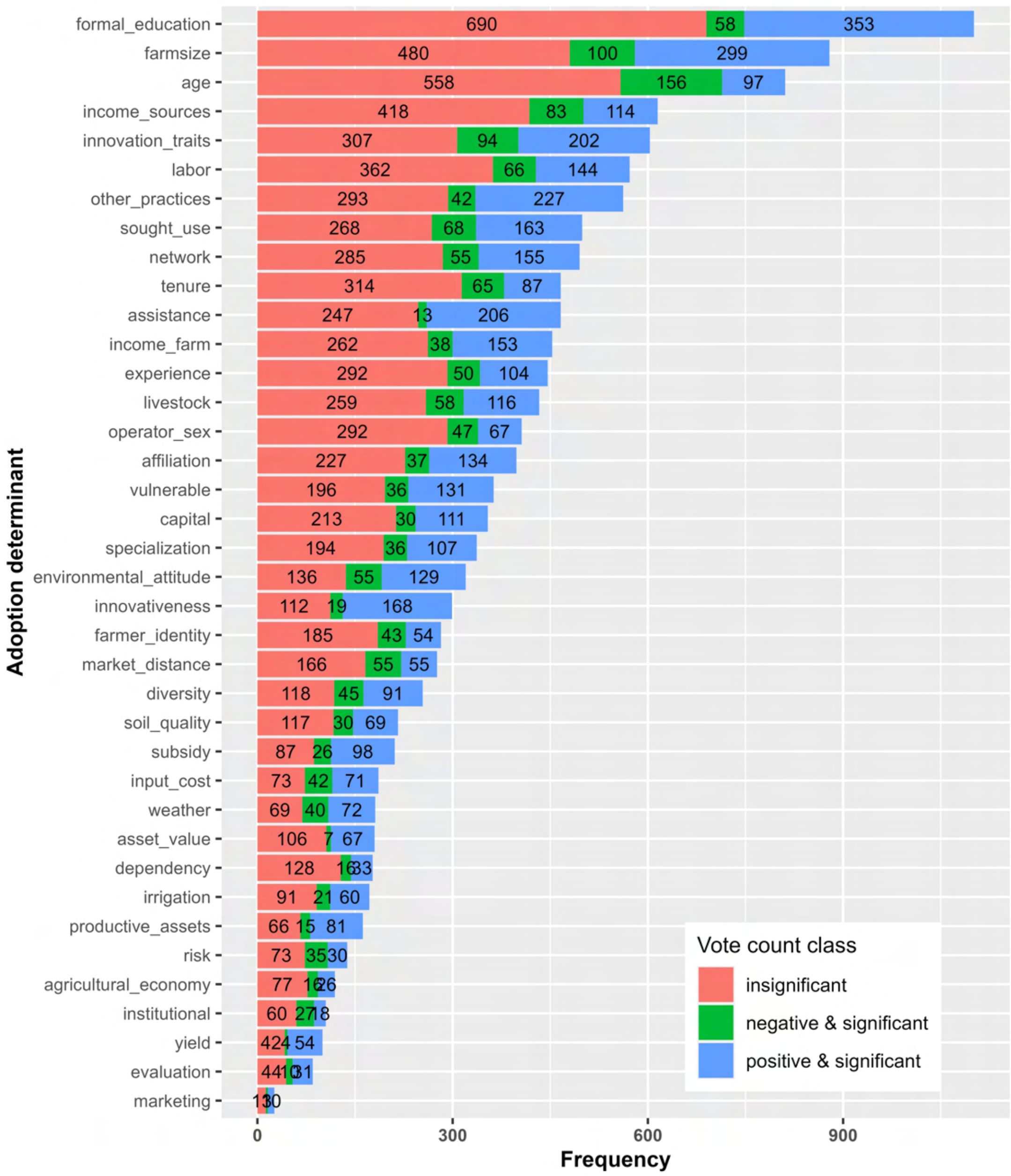

Figure 2.4: Frequency of adoption determinants by vote count class (full sample, n=13,748).

Note: This figure is based on the processed data (n=13,748). Non-usable observations and determinant categories without intuitive interpretation were excluded (*geography, interaction terms, other*).

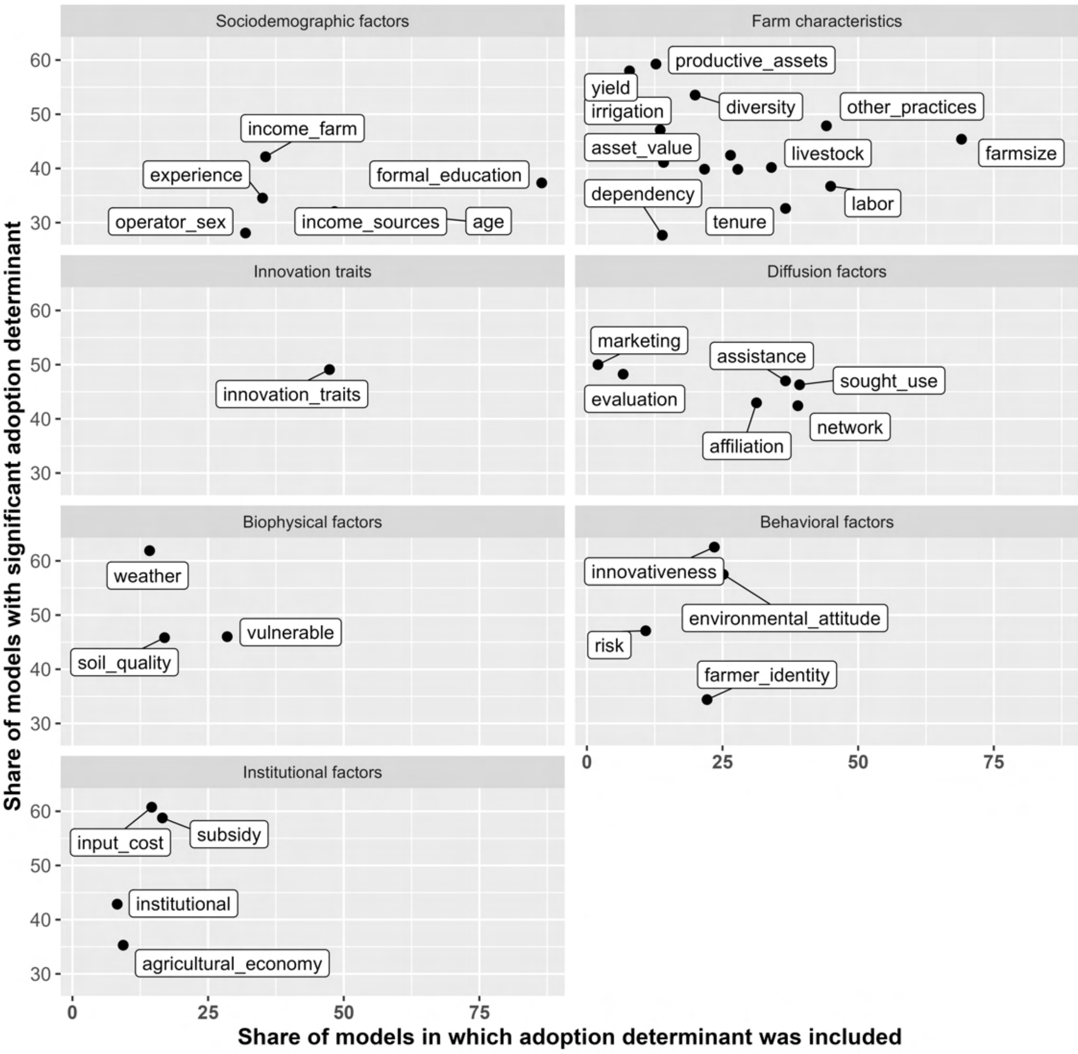

Figure 2.5: Share of adoption determinant inclusion and significance (full sample).

Note: The data underlying the plot can be found in Table A7 in the Supplementary Information.

The distribution of adoption determinants across the facets in Figure 2.5 underlines the previous finding that sociodemographic, farm-specific, and diffusion factors have received most attention in the adoption research in our sample when looking at the number of different variable conceptualizations. However, as discussed below, this does not necessarily mean that they bear disproportionate explanatory relevance in agricultural adoption research. We first look at variables which have often been included (>40%) but which were infrequently statistically significant (<40%). Three sociodemographic variables (formal education, age, income sources) and one farm characteristic (labor) were listed. Although these variables are often included as covariates in analyses their added benefit to scientific knowledge appears limited in light of their relatively infrequent significance in our sample. Regarding variables which were frequently included (>40%) and frequently statistically significant (>40%), two farm characteristics (farm size, other practices) and the variable innovation traits need mentioning. Arguably, these variables bear a relevant explanatory value for adoption research based on our sample and should thus be maintained in future agricultural adoption research. Among variables which were rarely included (<20%) but which were often found statistically significant (>40%), we identified farm characteristics (diversity, asset value, irrigation, productive assets, yield), a behavioral factor (risk), biophysical factors (soil quality, weather), institutional factors (subsidy, input cost, institutional) and diffusion factors (evaluation, marketing). These variables seem to play a relevant role in adoption research, as they were frequently significant when included in the models. However, we recorded only few data points to substantiate this statement. This motivates an interesting avenue for future research to develop and include more indicators in the mentioned categories, as they are likely to bear explanatory value when considered in adoption models. The remaining variables were infrequently included and infrequently found significant and are thus not discussed in detail here due to their arguably low information value for adoption research.

In the next step, we assessed the consistency of significance and impact direction of the recorded variables on adoption. Specifically, a conclusive two-proportion z-tests demonstrated that a tested variable was frequently found to be, e.g., statistically significant or positively associated with adoption. While columns two to five of Table 2.2 indicate for each variable the vote count classes and their sums, columns six and seven display the results of the consistency tests of significance and direction.

Regarding statistical significance, Table 2.2 complements the conjecture of Figure 2.4 since the majority of adoption determinants were either consistently insignificant (insig) or inconsistent (no entry). Thus, based on our sample, most covariates do not determine adoption in a statistically conclusive way. The test results for the variable direction support the notion of Figure 2.4 as well since 29 variables had a consistently positive association with adoption in this data set.

Table 2.2: Vote count analysis and results of consistency tests of significance and direction (full sample).

Adoption determinant	Sig-	Insig	Sig+	sum	Consistency of significance	Consistency of direction
Formal_education	58	690	353	1101	insig	pos
Farm size	100	480	299	879	insig	pos
Age	156	558	97	811	insig	neg
Income_sources	83	418	114	615	insig	pos
Innovation_traits	94	307	202	603		pos
Labor	66	362	144	572	insig	pos
Other_practices	42	293	227	562		pos
Sought_use	68	268	163	499		pos
Network	55	285	155	495	insig	pos
Tenure	65	314	87	466	insig	
Assistance	13	247	206	466		pos
Income_farm	38	262	153	453	insig	pos
Experience	50	292	104	446	insig	pos
Livestock	58	259	116	433	insig	pos
Operator_sex	47	292	67	406	insig	
Affiliation	37	227	134	398	insig	pos
Vulnerable	36	196	131	363		pos
Capital	30	213	111	354	insig	pos
Specialization	36	194	107	337	insig	pos
Environmental_ attitude	55	136	192	320	sig	pos
Innovativeness	19	112	168	299	sig	
Farmer_identity	43	185	54	282	insig	
Market_distance	55	166	55	276	insig	
Diversity	45	118	91	254		pos
Soil_quality	30	117	69	216		pos
Subsidy	26	87	98	211	sig	pos
Input_cost	42	73	71	186	sig	pos
Weather	40	69	72	181	sig	pos
Asset_value	7	106	67	180	insig	pos
Dependency	16	128	33	177	insig	pos
Irrigation	21	91	60	172		pos
Productive_assets	15	66	81	162	sig	pos
Risk	35	73	30	138		

continued . . .

. . . continued

Adoption determinant	**Sig+**	**Insig**	**Sig+**	**sum**	**Consistency of significance**	**Consistency of direction**
Agricultural_ economy	16	77	26	119	insig	
Institutional	27	60	18	105		
Yield	4	42	54	100		pos
Evaluation	10	44	31	85		pos
Marketing	3	13	10	26		n_small

Note: Sig -, Insig and Sig + represent the three vote count classes significant negative/positive and insignificant. Consistency tests: A cell containing information indicates that the test was significant (p<0.05) and that the adoption determinants were found to be consistent regarding their (in-) significance or direction. Empty cells represent an insignificant test results, i.e., a lack of consistency in significance or direction, and n_small indicates that the test was not conducted due to small number of observations.

Variables which were consistent regarding both their significance and impact direction on adoption stem from the groups of biophysical factors (weather), farm characteristics (productive assets), behavioral factors (environmental attitude, innovativeness), and institutional factors (subsidy, input cost). According to Figure 2.5, the here identified variables were significant disproportionately often; however, only a small share of models included them. Taken together, these results justify maintaining and further exploring these variables in future studies. Next, we look at variables which were consistent regarding their direction and insignificance. Except for two diffusion factors (network, affiliation), this category mainly contains sociodemographic variables (formal education, age, income sources, income farm, experience) and farm characteristics (farm size, labor, livestock, capital, specialization, asset value, dependency). As discussed in the context of Table 2.1 and Figure 2.4, the here subsumed variables were among the most frequently used variables across a broad spectrum of adoption research collected in our sample. This notwithstanding and in light of their consistent insignificance, they played no relevant role in determining adoption in our data set at this aggregation level.

Variables which were consistent regarding the positive sign but inconclusive regarding their significance originated in biophysical factors (soil quality, vulnerable), farm characteristics (diversity, irrigation, other practices, yield), diffusion factors (assistance, evaluation, sought/use) and innovation traits. Hence, despite unambiguous impact direction, a lack of consistency regarding significance indicates that for each adoption determinant the number of significant and insignificant observations were indistinguishable from one another. While this may hint at context-specific relevance of these covariates, no definite claim regarding their statistical relevance can be formulated at this point. However, with reference to Figure 2.5, several of the here listed variables were assessed in less than 20% of all models in our data, which may imply that more research is required to substantiate their statistical (in-) significance. Lastly, we turn to variables which were both inconclusive regarding the direction and inconclusive or insignificant regarding their significance. Here, we found farm characteristics (market distance, tenure), behavioral factors (farmer identity, risk), institutional factors (institutional, agricultural economy), one sociodemographic factor (operator sex), and one diffusion term (marketing). Since these variables were ambiguous regarding their direction and mostly insignificant, and since they were only included in the minority of recorded models except for operator sex and tenure (Figure 2.5), their informative value for adoption research is arguably low.

The results of this section are by and large in line with recent reviews (e.g., Borges et al., 2019; Thompson et al., 2023), i.e., a large share of determinants were sociodemographic and farm characteristics. Regarding significance, most variables were ambiguous or even consistently insignificant. In contrast to previous research, however, the majority of recorded variables showed a consistently positive association with adoption. The only six variables for which both direction and significance was consistent mostly originated from less researched variable categories. Furthermore, several variables with a high frequency of significant cases were not included in the majority of models. This observed imbalance of the frequencies of inclusion and significance of several variables may guide future research to pay more attention to the here identified determinants, as they possibly bear additional yet unexploited explanatory value.

2.4.3 Disaggregation by innovation types

We now turn to the disaggregated analysis according to innovation types. Table 2.3 presents the innovations assigned to their respective attribute(s) and the count of the associated adoption determinants extracted from primary publications. While the majority of observations were recorded for environmental footprint-reducing (A2) and productivity-increasing (A3) innovations followed by risk-reducing innovations (A1), the count of variables used to study the adoption of cognition-enhancing innovations (A4) was distinctly lower. The latter observation may be explained by the fact that only few innovations in primary literature matched our definition of cognition-enhancement in our collective coding approach (Text A5), and the count of observations is thus approximately proportional to the number of innovations per attribute. This also demonstrates that cognition-enhancing innovations, which we define to have components of data analysis and digital technology, have received less attention in the literature compiled in our data set; arguably, due to their relative novelty, complexity, and limited eligibility to countries with modern agricultural structures (also see Figure 2.3).

Table 2.3: Sample disaggregation according to innovation attributes.

Attribute	Sum	Innovations
A1 Rist-reducing	6,883	PF analysis support, PF intervention, insurance, fertilizer, improved seed, non-chemical biocide, soil analysis, chemical biocide, pest management, GMO, agroforestry, contract; n=12
A2 Environmental footprint-reducing	8,224	Nutrient optimization, PF intervention, conservation, contour, cover, tillage, buffer, non-chemical biocide, pest management, organic, agroforestry; n=11
A3 Productivity-increasing	8,059	Nutrient optimization, PF analysis support, PF intervention, fertilizer, improved seed, contour, cover, soil analysis, chemical biocide, mechanization; n=10
A4 Cognition-enhancing	1,328	PF analysis support, PF intervention, soil analysis; n=3

Note: Several innovations were assigned more than one attribute (Text A5, Table A4). The total number of observations in column two thus exceeds the sample size of the data base and several innovations occur more than once.

As for Section 2.4.2, we first looked at broader adoption determinant groups. Specifically, we aimed to find differences in the shares of adoption determinant categories used to study different innovation types as displayed in Figure 2.6. According to the bar chart, the shares of adoption determinant categories did not differ substantially between innovation types. Similar to the full data set, the most represented variable families—farm characteristics, sociodemographic factors and diffusion factors—add up to approximately 80% of all determinants used to assess adoption of these innovation types. For cognition-enhancing innovations, two slight differences in variable group shares were observed. While the share of diffusion factors (12%) ranked lowest for A4 innovations, the share of farm characteristics (42%) ranked highest compared to A1 to A3 innovations. One explanation could be that, according to our definition, A4 innovations may be more expensive in their acquisition compared to A1 to A3 innovations. Furthermore, higher complexity of on-farm implementation and inherently different characteristics of cognition-enhancing innovations pertaining to the technological infrastructure of farms may explain the emphasis of (economic) farm characteristics in the collected adoption research in this innovation group.

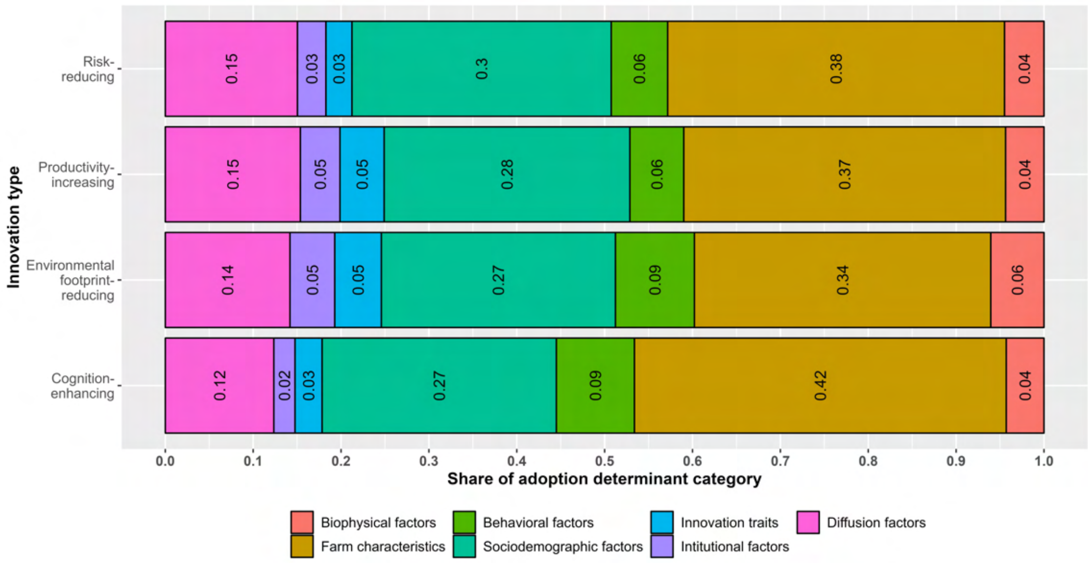

Figure 2.6: Share of adoption determinant categories by innovation type.

As in the aggregated analysis above, we next related the frequency in which each variable was tested to the frequency of being found significant to assess their informative values for adoption research. We maintained the disaggregated perspective to find systematic difference across the innovation-specific data sets. For commensurability, we restrict the discussion to protruding observations. The complete data and supplementary plots underlying the following analysis are presented in Table A8 and Figures A7 to A10.

With respect to farm characteristics, cognition-enhancing innovations stand out because the share of models which included the variables asset value, capital, dependency, labor, and market distance was distinctly lower for this innovation type (<5.5%) compared to models which assessed A1 to A3 innovations. Interestingly, in the few cases in which asset value was controlled for in A4 innovation type models, a majority thereof (80%) was significant. Conversely, the variables specialization and other practices were included disproportionately often in models of cognition-enhancing innovations

(>55%). However, the former variable was found statistically significant in fewer cases (<26%) in this innovation group, and the latter did not differ from other innovation types. In short, several covariates controlling for aspects of production factor endowments are underrepresented, while controls for specialization and use of related practices and technologies are relatively overrepresented in A4 innovations, although this is not reflected in notably different patterns in significance.

When looking at sociodemographic factors, cognition-enhancing innovations are noteworthy as well. Experience, income sources, and operator sex were tested distinctly less often in respective models compared to the other innovation types. Yet, finding at least experience to be frequently significant emphasizes the need to further explore this variable in the context of A4 innovations. Similarly, the variables age and farm income had higher shares of significant cases for cognition-enhancing innovations (>43%), highlighting their relative information values for adoption research compared to the other innovation types. This pattern continues for diffusion factors. Several variables, i.e., assistance, affiliation, and network, were tested disproportionally less often in cognition-enhancing innovation models. Assistance and affiliation were significant in distinctly fewer cases, suggesting that these variables contribute negligible information value for adoption of A4 innovations compared to A1 to A3 innovations in our data set. In turn, the variables evaluation and marketing, despite being included in very few models of A4 innovations, had a relatively higher share of significant cases compared to other innovation types. Again, these findings require further exploration since our data set does not contain enough cases to substantiate this observation.

Regarding behavioral factors, measures of environmental attitude and farmer identity were most often included in models testing environmental footprint-reducing innovations but were most often found significant for risk-reducing innovations. For cognition-enhancing innovations, environmental attitude was tested the least often, but innovativeness was controlled for most often. While we generally observed a lower frequency of behavioral variable usage, we found several pairs of specific innovations and behavioral variables which frequently became significant when included. Assessing this interaction between specific innovation types and related behavioral parameters may be another promising path for future research. We observed a similar result for institutional factors, i.e., generally low shares of models which included these variables but, when included in the models, frequently became significant.

Among biophysical factors, we tested and found the variable vulnerable to be significant disproportionally often in models assessing environmental footprint-reducing innovations. Lastly, measures of innovation traits showed a generally high level of significance (>45%) for all innovation types and were tested especially often in models assessing environmental footprint-reducing and productivity-increasing innovations adoption.

In the final step of this disaggregated analysis, we tested the consistency of direction and significance for each adoption determinant. Again, here we only discuss most notable findings from the comparison across innovation types (see Tables A9 to A13 for detailed results). The results of the aggregated sample (Table 2.2) were by and large reconfirmed. Most adoption determinants across innovation types displayed a congruent pattern–they tended to have a consistently positive yet insignificant association with adoption. A few variables, however, showed a discrepancy in the consistency of sign and/or significance, suggesting that the aggregated results masked heterogeneity of certain adoption determinants between the innovation types. Only one behavioral variable (innovativeness) was found to have a consistently significant and positive association with adoption in studies about multiple, i.e., risk-reducing, environmental footprint-reducing, and productivity-enhancing innovations. This implies that for the majority of innovation types, measures of innovativeness seem to play an important role in the included studies. Regarding the variable weather, which was consistently significant and positive in the full sample, the consistency in significance seems to be driven primarily by observations from studies on risk-reducing innovations, while the consistency in direction appears to stem from studies on environmental footprint-reducing and productivity-increasing innovations. Similarly, for the variable environmental attitude, the consistency in significance seems to be mainly driven by observations associated with risk-reducing innovation studies, while a consistently positive impact of this variable on adoption was driven by observations stemming from environmental footprint-reducing innovation studies. Moreover, risk-reducing innovation studies also seem to contribute the largest share of significant and positive observations to the determinants input cost and subsidy (institutional factors), which may explain the conclusive consistency test of significance and direction in the full sample. Lastly, while for most adoption determinants of cognition-enhancing innovations no consistency test could be calculated due to small samples size, one result stands out. Namely, the farm characteristic tenure (measures farming land ownership) was consistently negatively associated with the adoption of this innovation type, an observation which was not apparent in the full data set.

Disaggregation by innovation types revealed few additional yet interesting aspects. Our data base contains substantially fewer observations for cognition-enhancing innovations. This may be explained by their specific definition in our coding approach, their relative novelty, and applicability limited to contexts with modern agricultural structures. Nevertheless, several variables which were tested less often for A4 innovations displayed a higher share of significant cases compared to A1 to A3 innovations. In light of small subsample size, this finding requires cautious interpretation, but it also renders the exploration of the discussed variables a promising field in adoption research of digital farming innovations. Across all innovation types, we found that several institutional and behavioral variables, although included in the minority of models, showed a high share of significant cases. On the one hand, this is a strong argument for future studies to pay greater attention to these variables, as they seem to bear relevant explanatory value for adoption research in which they are currently underrepresented (Dessart et al., 2019). Additionally, although we acknowledge that our findings are purely observational in nature, they further emphasize the relevance to study the interplay of specific innovation traits and adoption determinants to get a more refined understanding of the conditions in which certain innovations are taken up by farmers (Blasch et al., 2022; Schulz and Börner, 2023). Specifically, measures of farmers' innovativeness were consistently significant determinants for most innovation types; variables of weather and environmental attitude as well as input cost and subsidy covariates were only consistent for risk-reducing innovations in our sample; and lastly, the association of controlling for land ownership (tenure) with adoption was consistently negative only for cognition-enhancing innovations.

2.4.4 Disaggregation by context

For the second disaggregation, we divided the sample into observations stemming from OECD and BRICS nations (n=7,736) and developing nations (n=6,012). Again, we first compared the relative distribution of adoption determinant groups across subsamples. Figure 2.7 reveals few contextual differences. The difference of eight percentage points in behavioral factors was most prominent, i.e., they were the least included variable group in developing country studies, while they ranked fourth in OECD and BRICS country studies. Furthermore, the share of diffusion factors was elevated by six percentage points in the developing country context compared to the OECD and BRICS sample. Taken together, these two findings suggest that the role of collaboration, exchange, and networks among farmers has relatively been rated more important in adoption research in developing countries, whereas attitudes and personality traits were more dominant in our sample of developed and emerging countries. The share differences of the remaining variable groups were even smaller and are not discussed any further.

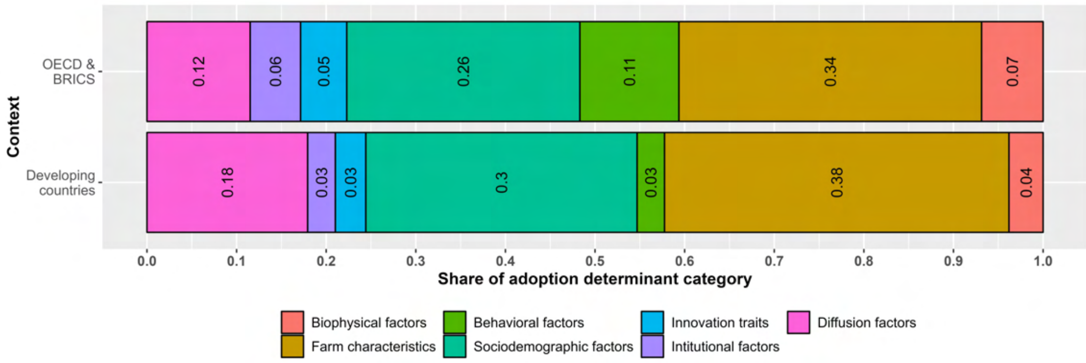

Figure 2.7: Shares of adoption determinant categories by study context.

Note: For the detailed disaggregated data underlying this visualization see Tables A14 and A15.

In going from their thematic categories to single determinant level, we now compare across the subsamples the proportions in which adoption determinants were included relative to their proportion of being found significant. This allows the depiction and comparison of their information value for adoption research in the given contexts. As before, we restrict the results description to prominent differences between subsamples (see Table A16 and Figures A11 and A12 for details).

Regarding farm variables, in OECD and BRICS countries the determinants asset value, dependency, and market distance were used relatively infrequently, but when included, they showed a high share of significant cases. The same holds for the variable diversity in the developing country context. These variables may thus be interesting candidates in future research in the respective contexts to verify or falsify their statistical relevance in a larger number of cases. Concerning the variable labor, a large difference regarding the shares of variable inclusion between contexts stands out, i.e., the variable was included in only 18% of models in an OECD and BRICS context compared to 87% of models based on developing country studies. Regarding coefficient significance, however, the samples showed a similar share of cases (39% and 36%, respectively). Clearly, in many studies based in developing countries, the degree of labor endowment was viewed to be an important adoption determinant, although this does not seem to be justified in light of modest shares of statistical significance. A similar pattern arises for the sociodemographic variables income sources and operator sex. They were included disproportionately often in studies in developing countries compared to the OECD and BRICS context, but the samples did not differ substantially in the shares of significant observations. This pattern continues in the group of diffusion factors where the variables affiliation, assistance, and network received much higher scholarly attention in developing context studies, although they had similar shares of significant cases compared to the OECD and BRICS data set. On a more general note, when included, all diffusion factors had a high share of significant cases above 40% in both contexts. Although for some variables this observation was based on few observations, this reiterates our previous line of argumentation in Section 2.4.3 regarding the potential to further explore diffusion factors in adoption research.

By contrast, behavioral variables were generally included less often in developing country studies (<16%) but, where included, they showed a disproportionately higher share of significant cases (>43%) compared to the OECD and BRICS sample. This is not to say that behavioral adoption determinants do not matter for the latter context. In both subsamples, high shares of significant cases indicate that behavioral determinants seem to play an important role in adoption research in a statistical sense. For biophysical factors, we highlight the variable soil quality. Compared to developing country studies, it was included distinctly less often in analyses (<14%) but was statistically significant in the majority of cases (>51%), thus suggesting itself a potentially insightful variable for future research based in OECD and BRICS countries. In the category of institutional variables, we highlight agricultural economy and institutional. While no substantial difference in the inclusion shares was present across the samples, the former (latter) had a much higher share of significant cases in studies with a focus on developing (OECD and BRICS) countries, which emphasizes their statistical relevance for adoption research in the respective context.

In a last step, we conducted the consistency tests of direction and significance of individual determinants and here discuss the most insightful differences arising from the comparison by context. Graphical and tabular details can be found in Tables A17 to

A19 and Figures A13 to A14. As above, the majority of determinants were consistently positive and a substantial share of cases was found either consistently insignificant or statistically inconsistent. However, there were four consistently significant and positive variables in OECD and BRICS country studies (input cost, productive assets, subsidy, weather), which were mostly inconsistent in the developing country context. In turn, we found the variable environmental attitude (yield) to be consistent regarding a positive association (positive association and significance) with adoption in the developing context but not in OECD and BRICS country studies. The only variable which was consistent regarding statistical significance and positive sign in both contexts was innovativeness. Thus, it becomes clear that several findings regarding the (in-) consistency of direction and significance in the full sample were driven to varying extents by the findings in the underlying contexts.

Similar to the attribute-specific analysis in Section 2.4.3, disaggregating by contexts yielded only few but notable findings. Relatively speaking, behavioral variables received higher scholarly emphasis in studies based in OECD and BRICS countries, while studies in the developing context, on average, deemed diffusion factors more important. In addition, regarding the inclusion frequency of several variables from the farm, sociodemographic, and diffusion variable categories, we observed imbalances which seem to be intuitively reasonable when considering their respective context. However, when matched with the assessment of determinant significance, a high (low) share of inclusion does not seem justified–often included variables were frequently insignificant and vice versa. Moreover, as for Sections 2.4.2 and 2.4.3, the results of the context-specific disaggregation show that, in contrast to relatively frequently included sociodemographic and farm variables, the determinants with most unambiguous statistical evidence predominantly stemmed from less frequently included variable categories, i.e., institutional, behavioral, and biophysical factors (Table A19). This furthers the demand to rebalance future assessments of adoption determinants toward context-specific covariates as they bear seemingly untapped yet valuable insights according to our findings.

2.5 Discussion

The present study provides an updated systematic global evidence map of a total of 13,748 adoption determinants recorded from 383 unique farm-level studies on the adoption of a broad spectrum of crop farming innovations. The first aim was to give an unbiased perspective on the current landscape of determinants used to explain observed agricultural adoption and thereby shed light on their seeming statistical importance relative to their inclusion frequency, and to identify promising variables for future research. The second aim was to assess potential sample heterogeneity by reanalyzing the data disaggregated by innovation attributes and by geographical context of primary studies. In the remaining Sections 2.5.1, 2.5.2 and 2.5.3, we briefly summarize the findings, discuss limitations of our study, and give an outlook for future research, respectively.

2.5.1 Summary of results

The majority of recorded adoption determinants were farm characteristics and sociodemographic variables, followed by diffusion and behavioral factors. while we recorded the least number of observations for biophysical, institutional, and characteristics referring to the innovation under study. On average, most variables had a positive association with adoption, although their impact was either consistently insignificant or ambiguous. Contrary to our expectation, nonetheless in line with Borges et al. (2019) and Schaub et al. (2023), this pattern did not change substantially in the disaggregated analyses. In the aggregate data set, we found only few variables which were consistent in significance and impact direction on adoption. They belong to the less or even least researched variable families of biophysical, institutional, and behavioral factors, thus rendering them interesting variable candidates for future adoption studies. Furthermore, we agree with previous scholars who have expressed the need for future research to primarily focus on behavioral and diffusion factors (Dessart et al., 2019; Hasler et al., 2017; Schaub et al., 2023; Thompson et al., 2023), which, when included in primary studies, had a statistically significant and positive effect on innovation adoption across our analyses.

Disaggregating by attributes revealed divergent patterns in variable inclusion and significance frequency. Specifically, several variables were tested distinctly less often in studies on cognition-enhancing, i.e., precision and smart farming innovations; however, we found them to be statistically significant in a higher share of cases. Furthermore, we found few yet interesting relations between certain innovation types and adoption determinants. We thereby confirm recommendations by de Oca Munguia and Llewellyn (2020) and Kuehne et al. (2017) to dedicate greater attention to the interaction between farmer and innovation-specific characteristics, as this may help to explain and predict which technologies are (not) taken up in specific contexts.

The context-specific analysis revealed systematic differences in the inclusion frequency of variables in most categories. While this pattern may be explained by intuitive economic reasoning, e.g., the distance to the next market or family labor endowment does arguably play an emphasized role for agricultural production in developing countries, we did not find notable evidence in a statistical sense to justify this and related statements. In fact, in both subsamples we found several variables to be poorly represented but statistically promising. Among those, even fewer were consistent in their positive impact on adoption and significance in one or even both contexts. Thus, we want to urge researchers to further explore the identified variable candidates, e.g., farmers' innovativeness and pro-environmental attitude or subsidies as behavioral and institutional variables, respectively.

2.5.2 Limitations

Several limitations in our study need to be addressed. First, while vote counting and consistency testing tolerate the inclusion of a multitude of different potentially incomparable model coefficients, which enables the collection of larger data sets, we base an important part of our discussion and conclusion on the evaluation of significances of effect estimates. However, p-values may not be sufficient to judge the relevance of model coefficients since they are arbitrary cut-off levels of statistical significance, and one should rather interpret the accuracy and size of effects (Amrhein et al., 2019; Heckelei et al., 2023). Although more rigorous meta-regression approaches come with their own limitations (Ruzzante et al., 2021; Schulz and Börner, 2023), they can yield more detailed insights about the relative importance of adoption determinants and thus be more valuable for policy recommendation. Furthermore, since we only included peer-reviewed quantitative literature, our findings may be prone to publication bias and may have systematically missed insights from qualitative literature which could have added to the understanding of farming innovation adoption (Dessart et al., 2019; Thompson et al., 2023).

Second, we did not assess whether the adoption model specification and theoretical underpinning of the included case studies had any influence on our findings since respective attempts presented in, e.g., Borges et al. (2019) or Wauters and Mathijs (2014) did not deliver further insights. Nevertheless, the choice of a specific adoption theory and regression model can have adverse effects. On the one hand, it may cause the systematic omission of potentially crucial variables, resulting in a biased effect of other covariates. On the other hand, a specific analytical framework may dictate the unsolicited pro forma inclusion of control variables without further adaptation to the study context, which may cause multicollinearity among covariates, thus leading to a distortion and/or insignificance of otherwise relevant adoption determinants (Borges et al., 2019). Neither did we analyze the effect of specific measurements and units of the dependent and independent variables in adoption studies. However, depicting adoption as a binary decision or a gradual process, recording education as binary (has education) or continuous (years of education), or seeing that environmental attitude can either be captured by a self-rated multi-item scale or recording whether a farmer voluntarily leaves land fallow, strongly suggests different dynamics in modeling innovation uptake (Schulz and Börner, 2023). We thus want to encourage future research to use our publicly available data base as a resource since it fortunately does contain respective (and further) information for each observation.

Third, our concept of innovation attributes may be incomplete for several reasons. Simplifying innovations' relative advantage by four stylized attributes disregards relative disadvantages arising from learning or investment cost (Li et al., 2018) or additional risk introduced by novel technologies (Sunding and Zilberman, 2001) which are prone to inaccurate or defective functionalities. Additionally, instead of a binary assignment of attributes, a more refined depiction thereof may be required, thereby allowing them to manifest in different intensities. Beyond that, a correlation of attributes with context-specific, e.g., socioeconomic or biophysical circumstances would be plausible (Khanna et al., 2022). This notion was explored in a meta-analysis in Schulz and Börner (2023), who found that adoption determinants vary in their relevance depending on the production factor abundance in a given socioeconomic contexts and the respective input factor demand of the innovation at stake.

The burgeoning literature on smart farming technologies increasingly presents autonomous robots and artificial intelligence as innovations which reduce physical strain and fatigue associated with manual work in agriculture and which increase convenience, well-being, and operator safety (Khanna, 2021; Kuehne et al., 2017; Marinoudi et al., 2019; Thompson et al., 2019). This characteristic is difficult to quantify and has overlaps with other attributes such as the enhancement of cognition and productivity. Additionally, due to the novelty of the associated innovations and limited availability of digital technology adoption research papers, it may be advisable to investigate this attribute on a case-study level rather than on meta-study level. Nonetheless, this characteristic can be expected to gain interest, as such technologies mature and are increasingly considered viable technology alternatives by innovative, well-educated farmers (Feisthauer et al., 2024a; Mohr and Kühl, 2021).

Fourth and last, we acknowledge that our findings are largely based on correlational case studies with no claim of causality. However, adoption studies based on perfectly controlled settings may suffer from a low degree of external validity, and we are therefore convinced that the large quantity of observations included in our data set can paint a relatively accurate picture of likely adoption dynamics, considering the resolution of our analysis.

2.5.3 Outlook

We identify promising yet less frequently investigated adoption determinant categories which need to be addressed in future adoption research. This notwithstanding, we confirm previous reviews, i.e., no unambiguous conclusions can be drawn for the majority of investigated variables. Although we add to the literature two further disaggregation approaches, our findings mostly persist throughout. Because the variety of innovations next to the socioeconomic, biophysical, and institutional contexts in which agricultural production takes place suggest limited comparability of individual adoption scenarios, the predominant inconclusiveness of our results may represent reality (de Oca Munguia and Llewellyn, 2020). Therefore, we want to discourage further comprehensive literature reviews with a scope as wide as ours and emphasize several research priorities. Although our conceptualization of innovation attributes did not yield the expected insights, we think it highly relevant to continue to investigate technology characteristics as adoption determinants because recent research continues to show that innovations are taken up out of other than purely monetary motives (Feisthauer et al., 2024b; Meijer et al., 2015). It further appears crucial to look at the intersection of specific innovations and farmer types who adopt them, given their respective environment. This will eventually enable the formulation of targeted policy recommendations to facilitate context-adapted promotion of sustainable innovations. Furthermore, adoption needs to be understood as a process rather than a binary decision (Schlüter et al., 2017; Weersink and Fulton, 2020). It is thus essential to get an in-depth understanding of driving and hindering factors at different stages of the process. This ties in with considerations in Shang et al. (2021) who state that adoption does not occur on one isolated farm since it is rooted in regional diffusion dynamics. Clearly, social norms, shared moral obligations and the influence of professional colleagues require consideration as determinants of location-specific patterns of diffusion (Feisthauer et al., 2024b; Hüttel et al., 2022).

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Conflicts of interest

There are no conflicts of interest.

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Supplementary Information

Supplementary Information can be found on the research group's project site with the Centre of Open Science (OSF) in the folder named according to the title of this chapter under this link: https://osf.io/uchte/?view_only=647d0e95b28a4b9d9c5462d31d6a761f

Data availability

The data can be found on the research group's project site of the Centre for Open Science (OSF) in the folder named according to the title of this chapter under this link: https://osf.io/uchte/?view_only=647d0e95b28a4b9d9c5462d31d6a761f. The R code for the analysis is available upon request.

2.6 References

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Chapter 3

Adoption intentions of smart weeding technologies–A lab-in-the-field experiment with German crop farmers[5]

Abstract: Smart weeding technologies (SWT) enable substantial herbicide savings via precise sensor-based application. This can enhance agrobiodiversity and make modern agriculture more sustainable. Currently, our knowledge about what will determine SWT adoption at the farm level is limited because few mature and economically viable prototype systems are available. We conduct a pre-registered and incentivecompatible online lab-in-the-field experiment with a convenience sample of 334 active German crop farmers to assess whether pro-environmental attitude, innovativeness, and trust in farming data privacy explain hypothetical SWT adoption. We further test if an environmentally motivated subsidy, a green nudge, and a combination thereof affect adoption intentions. While attitudinal measures clearly modulate hypothetical adoption decisions in our sample, we detect no effect for the nudge and subsidy. Our findings have implications for policy and future research. Substantial policy support may be needed as long as environmentally beneficial smart farming technology remains privately less competitive than conventional alternatives. Moreover, targeting criteria for early adopters include pro-environmental attitudes and innovativeness.

Keywords: Sustainable intensification, Attitudes, Subsidy, Nudge, Fractional multinomial logit

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JEL classification: Q16, Q18, D91

3.1 Introduction

In light of a growing global population and rising demand for bio-based food, energy, feed, and fibers, modern agriculture must boost eco-efficiency in order to sustainably ensure food security at global scale (von Braun et al., 2021). To intensify global food production sustainably, i.e. enhanced agricultural productivity with reduced environmental impacts thereof, no universal solution exists. Instead, a multitude of context-specific approaches must be pursued, often contingent on a wider systemic transformation process (Garnett et al., 2013). In particular, technological and management-related food system innovations bear considerable potential to counteract climate change and environmental degradation, for example, linked to farm input overuse (Springmann et al., 2018).

Smart farming technologies (SFT) are heralded as particularly promising innovations to reconcile environmental and productivity goals (e.g., Finger et al., 2019; Rübcke von Veltheim and Heise, 2021) and may trigger the 'fourth revolution' in agriculture (Walter et al., 2017). SFT are knowledge-intensive innovations based on agricultural machines that record and process data to make decisions in real time. By acting autonomously, SFT may gradually shift the operator's role away from active managerial tasks, such as steering machinery, toward supervising, adjusting, and intervening to resolve technical failures (Bovensiepen et al., 2016). Examples are robots for field operations like mechanical and chemical weeding, fertilization, pest detection (Rübcke von Veltheim and Heise, 2021), aerial inspection of crop nutritional status via hyperspectral cameras (Li et al., 2014), and drone-based pest scouting (Bovensiepen et al., 2016). The value proposition of SFT is to enhance the economic and environmental performance of agricultural production (Weersink et al., 2018). Specifically, SFT tailor field operations to the temporal and spatial field heterogeneity (Aubert et al., 2012; Wolfert et al., 2017), enabling substantial reductions in the use of chemical and other inputs (Finger et al., 2019; Sørensen et al., 2005), agricultural greenhouse gas emissions, and environmental pollution (Balafoutis et al., 2017). As such, SFT may appeal to farmers who are under pressure to balance trade-offs between profitability and environmental impacts in a range of agricultural production systems (Walter et al., 2017).

Lowenberg-DeBoer et al. (2020) demonstrated that automated and fully autonomous field robots can economically outperform conventional machinery for certain field operations. Nevertheless, on-farm experimental evidence is scant. Furthermore, while SFT may reduce negative environmental impacts, they also increase the complexity of agricultural systems (Scholz et al., 2021; Sparrow and Howard, 2021) and potentially pose data protection and sovereignty issues (Fleming et al., 2018; Jakku et al., 2019). The viability and speed of diffusion of specific novel technologies thus clearly vary depending on technology attributes, biophysical context and farmers' competences, and preferences (Finger, 2023; Khanna et al., 2022). Moreover, ethical and legislative concerns about unsupervised operations, automated agronomic data collection, and other genuinely novel characteristics inherent to SFT are likely to affect technology diffusion (Sparrow and Howard, 2021).

Past research on agricultural technology adoption has often focused on observable individual, farm, and contextual adoption determinants (Ruzzante et al., 2021; Shang et al., 2021; Tey and Brindal, 2012). This has greatly facilitated the identification of so-called 'early adopters' (Rogers, 2003), i.e. farm types among which innovation processes are likely to begin. However, given the novel SFT features discussed above, specific individual attitudes of farmers are likely to play a more important role in forming future adoption intentions and corresponding decisions than in the past. Yet, according to recent reviews, the available literature on sustainable farming innovations has so far paid only limited attention to behavioral factors (e.g., Dessart et al., 2019; Thompson et al., 2023). Exceptions include relatively recent studies that provide incipient evidence on how norms and attitudes toward the environment, innovations, and data privacy may interact with specific technology attributes (e.g., Blasch et al., 2022; Hüttel et al., 2022; Michels et al., 2020a; Mohr and Kühl, 2021). For example, in a choice experiment regarding Italian farmers' willingness to adopt precision farming technologies, Blasch et al. (2022) interacted, inter alia, the degree of automation and chemical savings with farmers' innovativeness and environmental preferences to find higher innovation willingness among farmers with higher attitude levels. Furthermore, Mohr and Kühl (2021) conducted a survey on behavioral determinants of the acceptance of agricultural artificial intelligence systems. While innovativeness was not a significant determinant in this study, a higher level of trust in property rights of farming data had a statistically significant positive effect on acceptance. To this point, however, no study has looked at the farmers' attitudes pertaining to their adoption intentions of data-intensive and (partly) autonomous SFT in a rigorous experimental setting. Additionally, a systematic analysis of the relationship between farmers' attitudes and policy scenarios to enhance SFT adoption is currently missing.

Thus, at this early stage, no general conclusions can be drawn on these interactions, and further case-specific evidence is needed to improve our understanding of the conditions under which farmers are willing to adopt SFT at relevant scales. In sum, expanding our knowledge base about how novel technology attributes align with farmers' sociodemographic and behavioral characteristics is essential to design effective enabling and regulatory frameworks for sustainable agriculture (Mizik, 2022; Sparrow and Howard, 2021; Thomas et al., 2019).

We address these knowledge gaps by focusing on smart weeding technologies (SWT), a branch of SFT with a relatively advanced level of technological development and high potential to increase herbicide use efficiency (King, 2017). The centerpiece of our online lab-in-the-field experiment with German arable farmers is an incentive-compatible two-period business simulation game in which we elicit innovation adoption intentions, i.e. the number of hectares allocated to SWT, from two perspectives. First, we analyze the relevance of attitudinal measures, based on prior literature, as additional covariates in order to address novel attributes inherent to SWT. Second, we test the effectiveness of hypothetical policy scenarios to positively influence adoption behavior. Specifically, we look at a subsidy and a green nudge, separately and in combination, as experimental treatments in a within- and between-subjects design.

Our contributions to the agricultural technology adoption literature are twofold. First, we move beyond economic feasibility assessment and shed light on attitudinal measures likely to bear additional explanatory value for the extent to which farmers do intend to adopt. We show that German farmers' pro-environmental attitude (AttEnv) and innovativeness are likely to matter for the technology diffusion process in the real world, whereas data concerns seem to be less of an adoption barrier. Our second original contribution lies in testing whether innovative policy instruments, namely, a conditional subsidy and a green nudge, can, separately and in combination, enhance adoption intentions. None of the policies investigated had a statistically significant effect on SFT adoption.

The following Section 3.2 details the conceptual background and research hypotheses after which Section 3.3 describes the empirical and analytical approach and gives an overview of the collected data set. Section 3.4 depicts the results of the analysis, and in Section 3.5, we discuss the results and conclude the paper in Section 3.6.

3.2 Conceptual background

Farmers' adoption decisions of sustainable innovations are known to be driven by monetary and non-monetary motives (Chouinard et al., 2008). Personal preferences and attitudes toward (sustainable) innovations can lead to managerial decisions that deviate from profit maximizing behavior (Musshoff and Hirschauer, 2014; Sattler and Nagel, 2010). SWT are associated with environmental benefits due to herbicide savings but are also less profitable than conventional weeding technology at current stages of development. Motivated by Annosi et al. (2019) and Aubert et al. (2012), we add to the set of sociodemographic adoption determinants three attitudinal constructs that are likely to interact with novel characteristics of SFT (exemplified by SWT) and assess whether these attitudes can explain farmers' willingness to partially forego private profits.

Both farmers' immediate profits and long-term livelihoods depend on the sustained quality of the natural environments. Therefore, managerial decisions are simultaneously driven by short-term economic goals and motivations to conserve natural resources (Blasch et al., 2022) in order to maintain long-term productivity (Chouinard et al., 2008) and environmental service provision (Juárez-Luis et al., 2018). Producers thus derive utility from innovations that enhance environmental quality, e.g., via the sustainable use of farm assets or in the form of aesthetic or recreational values (Chouinard et al., 2008). However, technologies that provide public environmental goods may also be adopted out of a desire to comply with social norms and expectations to improve one's reputation (Kuhfuss et al., 2016b) or because adoption comes with a 'warm glow' feeling (Andreoni, 1990). Lastly, as SWT can bring about substantial herbicide savings, mitigating environmental impacts, their uptake could be motivated by a farmer's general environmental concern or her perceived responsibility for the environment (Dessart et al., 2019). Hence, even though moving from conventional to SWT implies partially trading off short-term profits, we hypothesize that:

> **H1:** Farmers with a higher degree of pro-environmental attitude (AttEnv) allocate more hectares to environmentally friendly SWT than individuals with a lower degree of AttEnv.

Rogers (2003) describes early adopters as venturous, curious about innovations, and uncertainty-loving. Correspondingly, farmers who perceive themselves as interested and knowledgeable and who actively seek out information about technological innovations through the internet, magazines, or discussions with colleagues should be more likely to experiment with digital technologies. The literature on digital innovation adoption does not entirely confirm this conjecture though. While Michels et al. (2020b) found a positive association between stated innovativeness and smart phone ownership for farming purposes among German farmers, Beza et al. (2018) observed that personal innovativeness (PI) did not effectively promote intentions to use mobile SMS among Ethiopian farmers. One study conducted with Canadian farm managers identified innovativeness to favor the adoption of diagnostic and applicative precision agriculture tools (Aubert et al., 2012). Lastly, Mohr and Kühl (2021) provide a behavioral perspective on the acceptance of artificial intelligence systems among German farmers. While they found no direct effect of higher levels of personal innovativeness on acceptance, the former positively mediated a set of attitudinal measures which in turn indirectly affected acceptance in a positive way. Arguably, the relevance of farmers' innovativeness may vary across study designs and contexts. Especially for technologies with complex traits, such as SWT, innovativeness may be a necessary but not sufficient condition for adoption. For example, if innovative farmers are also well-informed about pending technological challenges of a particular digital technology, innovativeness may be associated with non-adoption. We hope to better understand this relation and hypothesize that:

> **H2:** Farmers with a higher degree of personal innovativeness (PI) allocate more hectares to environmentally friendly SWT than individuals with a lower degree of PI.

Many SFT have the ability to collect and process high-volume farming data, allowing them to take and continuously improve (semi-)autonomous analytical and operational tasks in real time (Bovensiepen et al., 2016). These novel technological features have sparked a controversial debate. Improved in-field decision-making based on artificial intelligence allows substantial chemical input reductions (Finger et al., 2019), and augmenting farming processes via big data applications will enhance foresight capacities and eventually transform whole farming business models (Wolfert et al., 2017). However, little quantitative research is available on how farmers evaluate the novel data-driven abilities of the 'digital brain' of SFT, let alone their effect on adoption intentions and implications for policies required to soothe concerns around big data in agriculture (Sparrow and Howard, 2021). Scholz et al. (2021) found that the agricultural digitalization process has raised growing concerns among farmers regarding the sovereignty, security, and ownership of their farming data, which may impose an impediment to the adoption of SFT (Fleming et al., 2018; Gabriel and Gandorfer, 2020; Jakku et al., 2019; Lioutas et al., 2019). We are aware of only one recent publication by Mohr and Kühl (2021), who quantified a positive relationship between 'farmers' expectation of property rights over business data' and the acceptance of artificial intelligence in agriculture. We shed further light on this relevant debate by explicitly considering the role of trust in the security and privacy of farming data for farmers' intentions to adopt SFT:

> **H3:** Farmers with a higher degree of trust in farming data security and privacy (DT) allocate more hectares to autonomous weeding robots (WR) as an alternative, environmentally friendly, weeding technology than individuals with a lower degree of DT.

The potential environmental benefits that are associated with the adoption of agricultural innovations may pose a rationale for policy intervention. Agri-environmental policy instruments, such as subsidies, can then increase the private profitability of innovations vis-à-vis established agricultural technologies to the benefit of society (Kuhfuss et al., 2016a; Musshoff and Hirschauer, 2014; Thomas et al., 2019). For example, in the framework of the EU's Common Agricultural Policy, agri-environmental policy incentives are designed to induce sustainable agricultural innovation by partially compensating the opportunity costs faced by farmers when adopting environmentally beneficial land uses (Kuhfuss et al., 2016a). Beyond compensation for the associated increase in production and transaction costs, subsidies signal societal appreciation to farmers, who are increasingly under pressure to align multiple and often conflicting sustainability demands (EEA, 2022). A technology-specific subsidy, even if not fully compensatory, may thus tip the balance in favor of the environmentally more beneficial, but privately less profitable technology option:

H4: A governmental subsidy increases the number of hectares allocated to environmentally friendlier SWT.

More recently, 'soft' policy tools (Akerlof and Kennedy, 2013) have been proposed to promote the adoption of sustainable practices and technologies. So-called behavioral nudges are designed to influence individuals' behavior toward more sustainable outcomes and thereby increase the welfare of an individual or (and) society at large (Congiu and Moscati, 2022). As such, nudges can be a cost-effective alternative to monetary incentive schemes. According to Thaler and Sunstein (2008), a nudge contains 'any aspect of choice architecture that alters behavior in a predictable way without forbidding alternatives or significantly changing economic incentives' (p. 6). While nudges are applied in a multitude of contexts (Akerlof and Kennedy, 2013; Thaler and Sunstein, 2008), 'green nudges' in particular aim at voluntary pro-environmental behavior change (Schubert, 2017). Ferrari et al. (2019) reviewed literature on the impact of green nudges on, inter alia, farmers' pro-environmental behavior and found that the majority of articles used two nudge design principles. Specifically, they either relied on salience and affect by addressing a novel issue of personal relevance to the nudged farmer or they made use of social norms and peer comparison.[6] Along these lines, nudges may be aimed at farmers' self-image (Howley and Ocean, 2022), their perceived responsibility toward the dominant social setting (Czap et al., 2015), or the environment (Peth et al., 2018).

However, the effectiveness of behavioral nudges depends on the specific context and behavior under consideration. For example, Buchholz et al. (2018) found that a green nudge significantly lowered participants' pesticide use, while Czap et al. (2019) showed that an empathy nudge (a personal message) significantly increased the number of Nebraska farmers enrolled in a conservation program. Kuhfuss et al. (2016b) confirmed the effect of a social norm nudge (comparison with other farmers) on intentions to maintain conservation practices in agri-environmental schemes, although this was contrasted by Howley and Ocean (2022), who showed that a similar social nudge had minimal effect on the intention to adopt smartphone apps for farming purposes. Lastly, in Czap et al. (2015), a heterogeneity analysis revealed that an empathy nudge was an effective intervention to increase hypothetical water conservation behavior only for those individuals who already showed higher pre-treatment conservation behavior. Potentially, any hint toward socially or environmentally desirable behavior might even have the

[6] See Blumenthal-Barby and Burroughs (2012) for a comprehensive review of nudge design principles.

opposite effect, i.e. farmers may react with protest behavior since for the adoption of costly innovations such as SWT substantiated support is needed. Despite the ambiguity in the empirical literature, we hypothesize based on the majority of study findings:

> **H5:** A green nudge increases the number of hectares allocated to the environmentally friendly SWT.

In the metaeconomics framework (MEF) and dual interest theory (DIT), Lynne et al. (2016) suggest that economic agents endeavor to find a balance between their (economic) self-interests and other business-related interests when considering outcomes of their managerial decisions. Other interests could be driven by the agents' empathy toward their social environment. The environmental benefits associated with SWT accrue to society at large as a public good. Thus, according to theory (Lynne et al., 2016), combined policy interventions that simultaneously address farmers' economic as well as farmers' societal interests can enhance conservation behavior more than each intervention separately. However, empirical literature testing the superiority of combining policy tools is both scarce and ambiguous. For example, Hagmann et al. (2019) found that a nudge to use green energy reduced the support for a carbon tax. However, experimental findings in Osman et al. (2021) and a review study by Stern (2011) suggest that combined monetary and non-monetary incentives were superior in increasing the consumption of sustainable food and reducing private carbon emissions, respectively, than each of the two incentive types in isolation. Despite several findings that nudges alone may not suffice to produce the desired effects (e.g., Czap et al., 2015; Peth et al., 2018; Reddy et al., 2020), research on combined policy effects is even more patchy in the context of agricultural technology adoption. Promisingly, Howley and Ocean (2022) tested two nudge types, an injunctive norm and social signaling, to find weak evidence that the combined nudge effect exceeded the sum of the individual effects on mobile phone farming app adoption by farmers in the United Kingdom. For the case of French farmers' enrolment in agri-environmental contracts, Kuhfuss et al. (2016a) showed that a financial incentive combined with an injunctive social norm was more effective and cost-efficient than a subsidy alone. Furthermore, a framed lab experiment in Czap et al. (2015) confirmed that the effect of a combination of a subsidy with an empathy nudge was larger than either of the individual treatment effects on hypothetical water conservation behavior. Accordingly, we formulate our last hypothesis:

H6: Combining monetary incentives and a green nudge leads to a higher number of hectares allocated to SWT than either of the two measures individually.

Note that hypothesis three only addresses WR. We argue that concerns around farming data security and privacy are mainly associated with fully autonomous WR, while the remaining hypotheses address both SWT investigated below.

3.3 Methods and data

3.3.1 Lab-in-the-field experiment–background and design

The novelty and low diffusion levels of SWT rule out an ex-post assessment based on observed adoption behavior under varying policy interventions for our case. Therefore, we designed a framed lab-in-the-field experiment (Gneezy and Imas, 2017; Thomas et al., 2019). Compared to costly controlled field experiments and ex-post observational studies with limited internal validity, lab-in-the-field experiments can be designed at relatively low cost and provide a high level of internal validity (Gneezy and Imas, 2017; Musshoff and Hirschauer, 2014). To maximize external validity, we addressed the study to non-standard subjects, i.e. active farmers (Gneezy and Imas, 2017). We framed the experimental setting to include information on the study context and practical agronomic decision tasks. Framing creates a common ground of contextual knowledge and aligns the (presumably diverging) implicit interpretations and assumptions of participants to the extent possible (Alekseev et al., 2017). Moreover, the experiment aimed to closely resemble a realistic decision situation, which is beneficial for data quality (Musshoff and Hirschauer, 2014). As such, the hypothetical nature of the experiment enabled us to study farmers' behavior in a scenario that assumed the commercial availability of SWT for crop farming and the presence of policy conditions tailored accordingly.

The pre-registered[7] and incentivized[8] study was programmed in Qualtrics and started out by recording a set of attitudinal measures. This order was chosen to obtain the attitudes unaffected by any information given throughout the experiment. To make hypotheses H1–H3 testable, we developed the three attitudinal measures based on multiple question items that were derived from the discussed literature and operationalized them via 7-point Likert scales on which study participants self-assessed their degree of (dis-) agreement. The final attitudinal constructs entered the analysis as standardized mean scores.[9]

This was followed by the experimental centerpiece—a two-period business simulation game. We collaborated with the Agricultural Chamber of North Rhine-Westphalia (NRW, a German federal state) for the development of experimental contents. After pretesting with eighteen chamber members (mostly active farmers), minor improvements regarding programming and farming terminology were implemented. Within the game, participants were placed in the role of fictitious farmers managing 50 hectares (ha) of arable land on which cereals and root crops would be cultivated and sold after each production period. The participant's task would be to choose between three weeding technologies—broadcast application (BC), spot spraying (SS), and a weeding robot (WR). Specifically, participants had to decide in each game period separately about the number of hectares allocated to each weeding technology. Only one technology could be allocated to each full hectare, i.e. repeated weeding or weeding fractions of hectares was not possible. On each hectare, two kinds of returns could be generated—economic and environmental—expressed in game points, which were converted into real Euros after

[7]Pre-registration: https://osf.io/b9ryz/?view_only=feba413987bf429d826ae8665eed15fc. The survey was part of a larger project. Only parts are used for the present study. The full survey, including formulations of attitudinal questions, business simulation game instruction, alongside sociodemographic and farm structural survey questions, can be found in the Online Appendix. The choice of two game rounds was motivated by a similar lab-in-the-field experimental study by Thomas et al. (2019). The decision on the hypothetical farm size of 50 ha was made after consultation with our partners in the Agricultural Chamber of NRW. Difficulties in achieving the minimum sample size required the acquisition of additional survey distribution channels in other federal states with different average farm sizes. However, for internal validity we maintained the original hypothetical farm size of 50 ha in the simulation game.

[8]The explanation of how the experiment was made incentive-compatible can be found at the end of the section.

[9]We tested the attitudinal constructs for internal consistency, yielding Cronbach's alpha values of 0.9 (AttEnv), 0.86 (PI), and 0.49 (DT). We are aware that the latter is below the acceptable level of 0.7. However, after dropping one item from the construct, yielding a Cronbach's alpha of 0.8, results and interpretations of all multivariate analyses remained robust. We thus decided to retain the original construct.

the game. Participants were informed that the three weeding technologies would perform equivalently in terms of weeding efficacy, but differently with respect to per-hectare gross margins and environmental impacts, and that all operations would be offered as a service per hectare by a contracting firm. BC served as the technological status quo. It was depicted as an established conventional weeding method with homogeneous chemical application, thus no additional benefits to the environment, but a comparatively high profit due to low operational costs. SS and the WR represented SWT alternatives associated with substantial chemical savings, thus providing environmental benefits via reduced impacts. However, these technologies were assumed to imply higher contracting costs and thus a lower profit margin for the farmer (Table 3.1).[10] While SS was depicted as an enhanced spraying boom mounted to a tractor with a human driver, the WR was framed as an autonomously operating SWT, thereby encapsulating the discussed unknowns of early-stage SFT, which allows us to test H3.

Table 3.1: Description of weeding technologies.

	Broadcast application	Spot spraying	Weeding robot
Steering mode	Tractor with human driver	Tractor with human driver	Autonomous
Profit margin (pts/ha)	90	66	66
Ecological value (pts/ha)	0	45	45

A key experimental design challenge lies in the parameterization of the absolute and relative private and environmental benefits of weeding technologies. First, no reliable information currently exists on the average profitability and environmental benefits of highly innovative SWT. Second, the experimental setting must allow participants to quickly calculate the payoff of alternative choices. This forced us to work with stylized values for private and ecological payoffs based on available knowledge. Several studies assessed relative yield performance in different crops by comparing broadcast herbicide application to SS or WRs (e.g., Gerhards and Oebel, 2005; Kunz et al., 2018; Sørensen et al., 2005) and yield losses in general due to reduced chemical weeding (e.g., Kobusch, 2003). Based on Pahmeyer et al. (2021) and the online production planning tool KTBL (2023), the relative profit loss of switching from BC to an SWT

[10] Based on discussions with experts (NRW Agricultural Chamber), we framed BC to be environmentally neutral instead of environmentally harmful to avoid irritation among participants, potentially leading to reduced participation willingness.

was found to range from 23 per cent to 62 per cent. Although the profit differences of switching from BC to SWT are mainly caused by lower average yields, equivalent weeding efficacy for all technologies was assumed for the parsimony of the simulation game. For commensurability and practicability, ecological values in Equation (3.2) are presented in the same unit to allow for comparison with private profits and illustrate the composition of societal utility. Private profit, ecological value, and total societal utility were calculated as follows:

$$Private\ profit = 90 \times \mathrm{ha_{BC}} + 66 \times \mathrm{ha_{SS}} + 66 \times \mathrm{ha_{WR}}, \tag{3.1}$$

$$\text{with } \mathrm{ha_{BC}} + \mathrm{ha_{SS}} + \mathrm{ha_{WR}} = 50\ \mathrm{ha}$$

$$Ecological\ value = 45 \times \mathrm{ha_{SS}} + 45 \times \mathrm{ha_{WR}}, \tag{3.2}$$

$$Total\ societal\ utility = private\ profit + ecological\ value. \tag{3.3}$$

In the first round (baseline) of the experiment, all participants played the same game. Equations (3.1)-(3.3) were shown to each participant, followed by the task of setting up their baseline weed management plan. Thereafter, participants were shown their individual outcomes in terms of private profit, ecological value, and total societal utility. In the following round two (treatment round), participants were randomly assigned to one of the four experimental conditions (Table 3.2).

Table 3.2: Randomized assignment of experimental conditions to treatment groups.

	Subsidy = 0	**Subsidy = 1**
Nudge = 0	T_0	T_1
Nudge = 1	T_2	T_3

Prior to deciding on their weeding strategy for round two, each treatment group received a different informational text. The control group T_0 received a text without any connection to the experiment. In line with H4, treatment group T_1 was informed that they would obtain a subsidy of ten points for each hectare weeded with SS or WR. This partially compensated farmers' opportunity costs of switching from broadcast to a more sustainable but less profitable technology. Group T_1 was thus shown an updated private profit function (Equation (3.4)).

$$Private\,profit_{(T1)} = 90 \times \mathrm{ha}_{\mathrm{BC}} + 66 \times \mathrm{ha}_{\mathrm{SS}} + 66 \times \mathrm{ha}_{\mathrm{WR}} + 10 \times (\mathrm{ha}_{\mathrm{SS}} + \mathrm{ha}_{\mathrm{WR}}) \tag{3.4}$$

The calculation of ecological benefits remained identical to Equation (3.2). Respondents were informed that societal utility did not include the values of the subsidies; thus, social utility equaled environmental benefits and private profits, excluding subsidies. According to H5, the green nudge, shown to participants of treatment group T_2, appealed to the intrinsic motivation of farmers as environmental stewards and key actors in guaranteeing safe and sustained food production, highlighting farmers' responsibility for the welfare of society as a whole via voluntary sustainable practices. Thereby, the nudge made use of the salience and affect design principle (Blumenthal-Barby and Burroughs, 2012).[11] Profit, ecological, and societal utility per hectare were kept at baseline levels. Finally, treatment group T_3 received treatment texts T_1 and T_2 in combination (H6) alongside the formulae for the calculations of returns as shown to treatment group T_1. After receiving one of the treatment texts and updated information regarding the calculation of their profits, participants set up their weeding plan again, followed by the display of their respective private, ecological, and societal outcomes. Subsequent to the business simulation game, information on sociodemographic and farm structural variables was collected.

Lastly, and only upon finishing the whole survey, respondents could insert their email address to redeem their incentive, which consisted of the countervalue of their economic and ecological benefits from one of the two randomly selected game periods. The profit obtained in that round was converted (150 points = 1 Euro) into a voucher from a workwear retailer and sent out to all farmers who provided their e-mail address. The ecological benefit was converted at the same rate into a donation. For donations, we chose organizations or initiatives that contributed to promoting environmental goals, such as the multifunctionality of rural agricultural landscapes, in the respective German

[11]The exact wording of the environmental nudge was (translated from German): 'In their daily work, farmers realize the principles of good agricultural practice in manifold ways. Besides the production of safe and healthy food and other agricultural products, this also means that they cater to a careful handling of the environment and natural resources. The usage of innovative and herbicide saving technologies offers farmers an additional opportunity to contribute to a more sustainable agriculture. Thus, they promote the stability of ecosystems and the protection of biodiversity. Thereby, the sum of individual farmers decisions can significantly enhance the well-being of society and the security of the natural basis of life for current and future generations.'

federal state of the participant. The respective information regarding the pay-out was provided to participants prior to conducting the experiment. Depending on participants in-game decisions, voucher values and donations could range from 22 Euros (show-up fee) to 30 Euros and from 0 Euros to 15 Euros, respectively.

3.3.2 Analysis

3.3.2.1 *Attitudinal measures*

First, we assess baseline determinants of SWT allocation shares. While controlling for sociodemographic variables, we mainly focus on attitudinal constructs such as AttEnv, PI, and trust in farming data security and privacy to address hypotheses H1-H3. Let y_{ij} be the amount of hectares farmer *i* allocates to weeding technology *j* such that the normalized allocation shares are given by $s_{ij} = y_{ij}/50$. By construction, allocation shares lie between zero and one and have to sum up to unity for each farmer i. This characteristic of the outcome variables motivates a fractional multinomial logit model (FMNL), the multivariate extension of the bivariate fractional logit model presented in Papke and Wooldridge (1996). The FMNL framework has no assumptions regarding the distribution of outcome variables. This allows for extreme values of zero and one at non-trivial probability, i.e. allocations of zero or 50 ha to one particular technology (which are contained in our data set) can be included (Mullahy, 2015). However, the FMNL assumes independence of irrelevant alternatives (IIA), implying that the ratio of two alternatives is unaffected by the characteristics of other options. This may be inconsistent with the unit-sum share in the FMNL, but the varying implicit attributes introduced by our framing render our three weeding options mutually exclusive (Murteira and Ramalho, 2016).[12] We are therefore not concerned about inferential issues related to the IIA assumption. The conditional expectation of technology land shares s_{ij} is expressed as follows (e.g., Ji and Cobourn, 2018; Mullahy, 2015; Wang and McCarl, 2021):

[12]Murteira and Ramalho (2016) discuss the Dirichlet-Multinomial (DM) model as an alternative fractional response modeling approach. While the DM model is more flexible, it is not as robust to misspecification as the FMNL is (Becker, 2014). Moreover, the DM requires assumptions about the distribution of shares, a condition that rarely holds in practice (Becker, 2014). When comparing both approaches, Murteira and Ramalho (2016) found only slight efficiency advantages of the DM. In another comparison, Mullahy (2015) found that the APEs did not differ substantially and concluded that the DM model does not come with particular benefits over the FMNL. We thus opted for the FMNL as the main modeling framework for our study.

$$E\left[s_{ij}|\mathbf{x}_i\right] = G_j\left(\mathbf{x}_i;\boldsymbol{\beta}_j\right) = \frac{\exp\left(\mathbf{x}_i\boldsymbol{\beta}_j\right)}{\sum_{k=1}^{J}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_k\right)};\ j = 1, 2, 3. \tag{3.5}$$

In Equation (3.5), $G_j(\boldsymbol{x}_i;\boldsymbol{\beta}_j)$ is the multinomial logit link function and contains $\boldsymbol{\beta}_j$ and $\boldsymbol{x}_i$ to capture the technology-specific parameter vector and farmer-specific control variables, respectively. Setting technology *J* (BC) as the reference category (normalization of $\boldsymbol{\beta}_J$=0) further yields for the reference technology *J* (Equation (3.6)) and all other technologies *j* (Equation (3.7)), respectively:

$$E\left[s_{iJ}|\mathbf{x}_i\right] = G_J\left(\mathbf{x}_i;\boldsymbol{\beta}_J\right) = \frac{1}{1+\sum_{k=1}^{J-1}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_k\right)}; \tag{3.6}$$

$$E\left[s_{ij}|\mathbf{x}_i\right] = G_j\left(\mathbf{x}_i;\boldsymbol{\beta}_j\right) = \frac{\exp\left(\mathbf{x}_i\boldsymbol{\beta}_j\right)}{1+\sum_{k=1}^{J-1}\exp\left(\mathbf{x}_i\boldsymbol{\beta}_k\right)};\ j = 1, ..., J-1. \tag{3.7}$$

The exact empirical model specification is given by Equation (3.8) in which $G_j^{-1}(\boldsymbol{x}_i;\boldsymbol{\beta}_j)$ is the inverse of Equation (3.5), with μ_j being the intercept, $\boldsymbol{\beta}_j$ being the technology-specific parameter vector, and $\boldsymbol{X}_i$ a matrix of farmer characteristics including sociodemographic and, the main interest of the baseline analysis, attitudinal constructs. The error term is represented by ϵ_{ij}.

$$G^{-1}(\mathbf{x}_i;\boldsymbol{\beta}_j) = \mu_j + \boldsymbol{\beta}_j\mathbf{X}_i + \epsilon_{ij} \tag{3.8}$$

The functional specification of the FMNL requires a quasi-maximum likelihood estimation (QMLE) procedure (Papke and Wooldridge, 1996). Assuming the link is correctly specified, the QMLE yields a consistent and asymptotically normal estimator $\hat{\boldsymbol{\beta}}$. Estimated model coefficients represent effects on the log-odds ratios, i.e. the effect of a one-unit change in a covariate on the log of the probability of choosing technology *j* over the reference technology *J*. We calculate average partial effects (APEs), which represent the effects of a unit change in a continuous explanatory variable on s_{ij}, the observed share of land farmer *i* dedicates to technology *j*, while all other explanatory variables are held constant at the sample mean. APEs for discrete explanatory variables are interpreted as the effect on s_{ij} due to a change of a covariate from minimum to maximum. The sum of APEs across technology shares for a given covariate yields zero by construction (Mullahy, 2015). Reported standard errors of APEs are calculated via the Krinsky–Robb algorithm (Papke and Wooldridge, 1996).

3.3.2.2 *Policy treatment effects*

To assess the effect of hypothetical policy scenarios (treatments) on weeding decisions (H4–H6), we adopt the same FMNL approach as above. However, we extend the functional specification (Equation (3.9)) to include three dummies to account for treatments T_1 and T_2 individually and their combination T_3:

$$G^{-1}(\mathbf{x}_i;\boldsymbol{\beta}_j) = \mu_j + \boldsymbol{\beta}_j\mathbf{X}_i + \boldsymbol{\gamma}_{1j}T_1 + \boldsymbol{\gamma}_{2j}T_2 + \boldsymbol{\gamma}_{3j}T_3 + \epsilon_{ij} \tag{3.9}$$

Coefficients γ_{1j-3j} are policy scenario coefficients and capture the effect of a respective policy treatment on area allocation to the *j*'th weeding technology. APEs are calculated as above. Figure 3.1 depicts the design of the business simulation game.

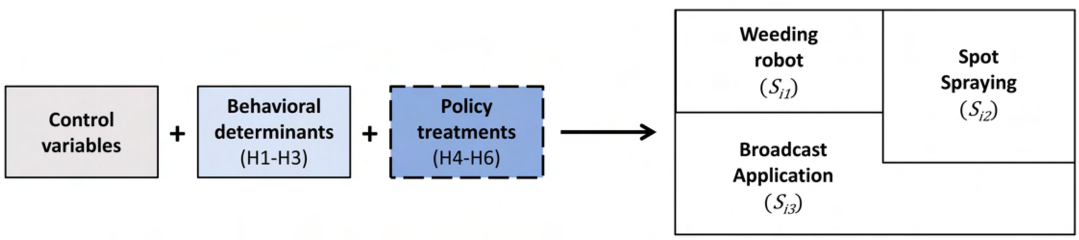

Figure 3.1: Visualization of business simulation game.

Note: Control variables and behavioral determinants (solid border) enter the analysis in both rounds; policy treatments (dotted border) enter the analysis only in round two. S_{i1}, S_{i2}, and S_{i3} represent the allocation shares associated with the respective weeding technology, as given in Equation (3.5).

3.3.3 Data

Data were collected between February and April 2022. We conducted an ex-ante power analysis based on a reference study with a comparable experimental setup to calculate the minimum required sample size.[13]

[13]The linear regression model in Thomas et al. (2019) yielded an R^2 of 0.12 which translated to a Cohen's f^2 of 0.136 representing a 'small' effect size. To detect such an effect size with a significance level of 0.05 and a power of 0.9 we would require at least 215 observations.

The email invitation to the survey was sent out via multiple channels, including farmers' representatives of several German federal states and training farms (Tables S1 and S2). In total, 713 farmers started the survey by clicking on the invitation link. We excluded all participants who did not finish the study (n = 336; dropout rate = 47.1 per cent), those who did not grant us consent to use their anonymized experimental responses (n=3), and those who answered a question about their understanding of the experimental instructions incorrectly (n = 40). The final data set consisted of 334 complete responses (Table 3.3). The average survey duration was 106 minutes and the mean values of vouchers and environmental donations were 25.7 and 9.2 Euros, respectively.

Table 3.3: Selected sociodemographic and farm-structural sample characteristics.

	Sample (SD)	**German farmer population**[a]
Age in years	43.3 (11.9)	53.0
Gender	90.0 per cent male	64.0 per cent male (full-time & part-time farmers), 89.0 per cent (full-time farmers only)
Farming experience in years	24.0 (12.7)	N/A
Full-time farming	82.0 per cent	41.8 per cent
Family farm	92.0 per cent	41.8 per cent
Farming style	83.0 per cent conventional	90.1 per cent conventional
Farm size (ha)[b]		
0-5	0.9 per cent	-
6-10	1.8 per cent	-
11-20	5.7 per cent	-
21-50	16.0 per cent	-
51-100	28.0 per cent	-
101-200	33.0 per cent	-
>200	15.0 per cent	-
Education	60.0 per cent vocational training, state-approved/master's certificate; 37.0 per cent Bachelor/Master degree, 0.9 per cent doctoral degree; 1.8 per cent none	58.0 per cent vocational training, state-approved/master's certificate; 9.0 per cent Bachelor/Master/ doctoral degree; 33.0 per cent other
Experience with SFT	32.0 per cent	N/A

n = 334

[a] See the Online Appendix for references used for comparison.

[b] Due to substantial differences in farming structures across different German federal states, it did not appear feasible to calculate and present shares of different farm size classes of the German farmer population averaged across all federal states. Average farm sizes per federal state can be found in the additional references in the Online Appendix.

On average, our sample was about ten years younger than the average of the German farmer population. Presumably, younger farmers are more likely to regularly use a computer and thus participate in online surveys distributed through email. The share of male participants was clearly above the German average of 64.0 per cent of male farm workers. However, when assuming that participants were farm owners, the sample closely resembles the German average of 89.0 per cent male farm owners. The share of full-time farmers is twice as high as the German average (41.6 per cent), while family farms are only slightly overrepresented relative to the respective German population (86.7 per cent). With respect to farm size, we found disproportionately large farms in our sample, i.e. 75.0 per cent (47.0 per cent) of our sample cultivated 51.0 (101.0) or more ha (91.0 per cent of the participants originated in the federal states of North Rhine-Westphalia, Bavaria, Baden-Wuerttemberg and Lower Saxony with respective average farm sizes of 43.8, 36.0, 36.6, and 72.7 ha in the underlying populations).

Presumably, larger farms boast a higher degree of digitalization (Fleming et al., 2018) and may thus be more inclined to participate in online surveys. Compared to the nationwide average (90.1 per cent), conventional farmers were underrepresented in our sample, possibly due to the appeal that the technological context of our study might have had on farmers with an interest for sustainable herbicide-saving technologies. We found that our sample was disproportionately well educated. About 38.0 per cent had an academic degree in a related field. Finally, 32.0 per cent of all participants had prior experience with SFT. In light of the online mode of distribution and participation, respective distribution channels, and lack of representativeness of descriptive statistics, the present sample must be regarded as a convenience sample (Ellis et al., 2023), and the findings of subsequent analyses may not necessarily hold for the general German farmer population. However, in line with Hüttel et al. (2022), we argue that it represents a relevant group whose behavior may be illustrative of likely behavior of potential early adopters.

3.4 Results

3.4.1 Descriptive analysis

In the baseline, mean area allocation was 23.4 (BC), 17.4 (SS), and 9.1 (WR) ha for the full sample, indicating a general preference for BC and SS over the WR (Figure 3.2). As expected, neither a Kruskall–Wallis rank sum test nor pairwise Mann–Whitney U tests point to significant differences in weeding decisions between the treatment groups (Tables S5–S8). Furthermore, we conducted Kruskall–Wallis rank sum tests and Pearson's Chi-squared tests to ascertain the balancing of continuous and binary control variables (sociodemographic, attitudinal, and farm structural variables) across treatment groups, yielding no significant differences. We can thus assume adequate randomization of treatments among participants in our sample (Table S16).

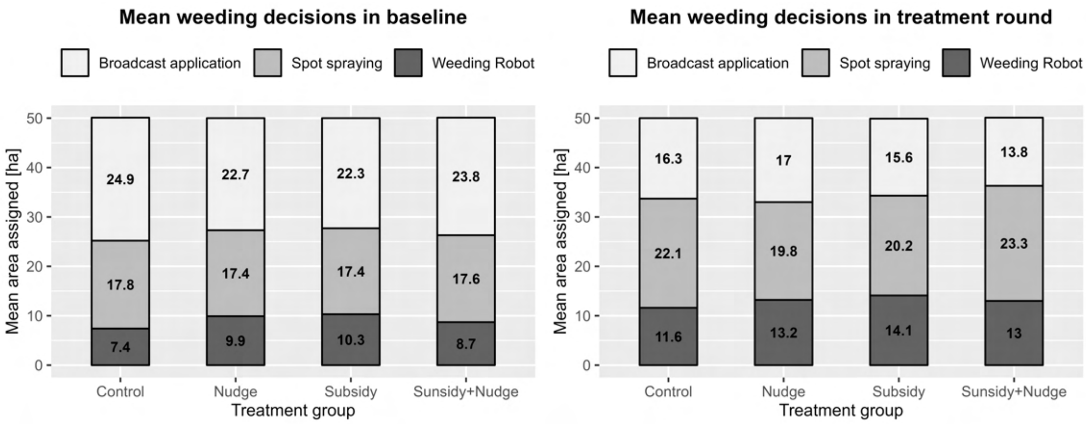

Figure 3.2: Mean weeding decisions in baseline and treatment round.

Mean technology allocations in the treatment round are surprising (Figure 3.2). On average, participants allocated 15.7, 21.3, and 13.0 ha to BC, SS, and WR, respectively, indicating a substantial switch toward SS and WR from the baseline to the treatment round (Table 3.4). P-values of <0.001 from Wilcoxon rank sum tests imply statistically highly significant differences in technology choices between rounds; also see Table S3. This is confirmed by a statistically significant Wilcoxon-signed rank tests of within-group differences between rounds. Inspecting average weeding decisions per treatment group and comparing baseline and treatment rounds reveals that all groups, including the control group, show similar switching behavior (Table S4).

Another Kruskal–Wallis rank sum test and pairwise Mann–Whitney U tests on treatment round results yield no significant differences between groups (Tables S9–S12). We further discuss this unusually large round effect below. Lastly, we calculated the changes in each weeding technology allocation for each group and tested them with pairwise Mann–Whitney U tests. No significant differences in the allocation changes were found (Tables S13–S15).

Table 3.4: Average change of weeding technology allocation from round one to round two.

	Technology allocation change (ha)			
Weeding technology	**Control group**	**Subsidy**	**Nudge**	**Subsidy + Nudge**
Broadcast application	-8.6	-6.7	-5.7	-10.0
Spot spraying	4.3	2.8	2.4	5.7
Weeding robot	4.2	3.3	3.8	4.3

3.4.2 Multivariate analysis

The controlled hypothetical setting, in principle, allows us to focus on treatments and sociodemographic as well as attitudinal measures in a parsimonious model specification.[14] Moreover, to account for multicollinearity, we dropped less informative covariates if their absolute correlation with any other covariate was 0.3 or higher (Table S17). AttEnv and PI (correlation of 0.37) are an exception to this rule in order to test for H1 and H2. Lastly, we dropped gender as a covariate given the fact that respondents are predominantly male. Sociodemographic variables were included as controls in all analyses.

3.4.2.1 *Attitudinal measures*

We start by looking at pre-treatment determinants of SWT allocation shares as per the FMNL regression.[15] Figure 3.3 presents APEs of the attitudinal constructs. A one-standard deviation increase in AttEnv is significantly associated with a 3.3 per cent (1.7 ha) WR area increase and a 5 per cent (2.5 ha) decrease in BC area allocation. By contrast, a standard deviation increase in PI is significantly associated with a 4 per

[14]The pre-registration foresaw including farm structural variables. However, excluding them had no major qualitative effect on the coefficients of main interest which justified the parsimonious model above.

[15]See Table A18 for an additional Tobit regression as foreseen by the pre-registered analysis plan.

cent (2 ha) increase in SS and a 6.1 per cent (3.1 ha) decrease in BC. Together, the baseline FMNL results support H1 and H2, i.e. AttEnv and PI significantly increase SWT adoption levels while broadcast usage is reduced. The APEs for the data trust construct are close to zero and statistically insignificant for all technologies (Table S19).

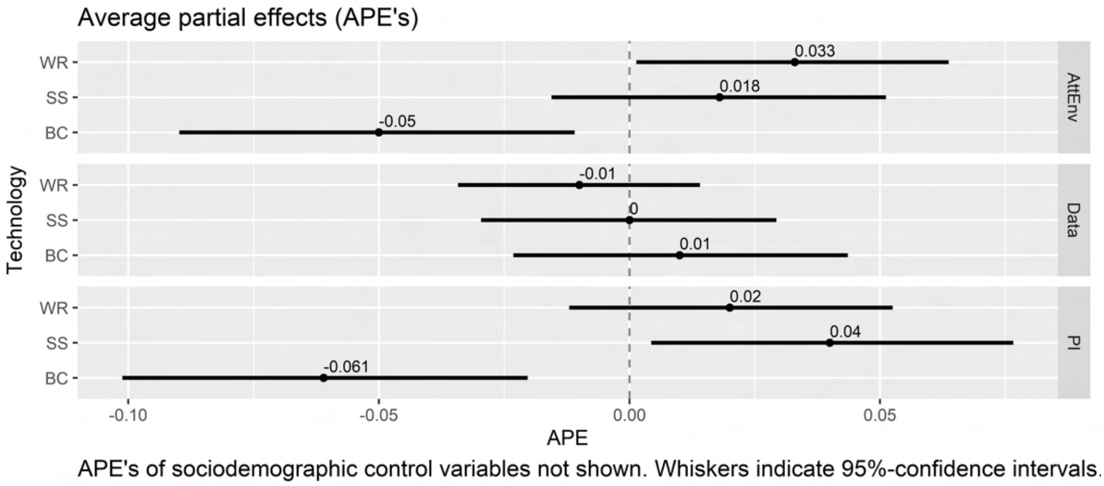

Figure 3.3: Baseline determinants of technology allocation shares (FMNL).

Note: AttEnv, pro-environmental attitude; PI, personal innovativeness; Data, trust in farming data security and privacy; BC, broadcast application; SS, spot spraying; WR, weeding robot.

3.4.2.2 *Policy treatment effects*

To assess the effectiveness of hypothetical policy scenarios, we ran another FMNL regression for the treatment round outcomes. The statistical pattern of attitudinal constructs remains robust compared to the baseline (Table S20). Figure 3.4 shows the APEs of policy scenarios on technology allocation shares. None of the policy treatments, i.e. the subsidy (H4), the nudge (H5), and their combination (H6), have a statistically significant effect on technology choice, and the large confidence intervals indicate considerable variability in responses. The signs of the respective APEs are in line with the hypotheses nonetheless. It is possible that unexplained variation in our model masks a relevant relationship between the policy treatments and hypothetical SWT adoption (Amrhein et al., 2019). While we acknowledge that the estimates are statistically indistinguishable from zero, the magnitudes of the estimated APEs for policy treatments suggest changes in area allocation in the order of 2 ha on average, which constitutes a potentially relevant relationship that merits further research. While T_1 and T_2 are mainly associated with higher (lower) area allocations to WR (SS), T_3 correlates positively with area allocations to both SWT options.

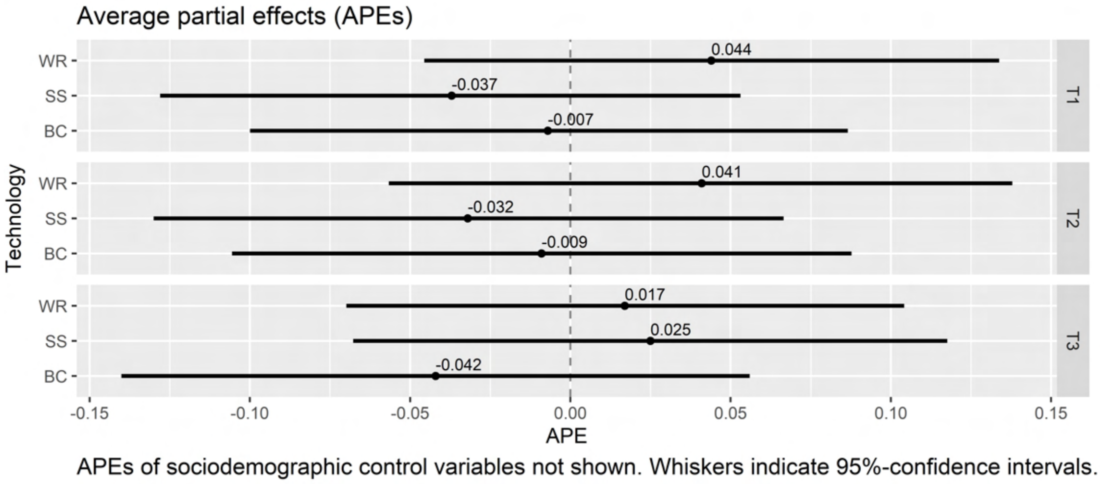

Figure 3.4: Treatment round determinants of technology allocation shares (FMNL).

Note: T_1, subsidy; T_2, nudge; T_3, subsidy + nudge; BC, broadcast application; SS, spot spraying; WR, weeding robot.

3.4.2.3 *Exploratory analyses*

The apparent round effect on technology allocations across all participant groups merits further scrutiny. Following Ji and Cobourn (2018), we used a pooled cross-sectional FMNL specification including a game round dummy (R_t) to capture temporal dynamics in our two-period experiment. Moreover, we clustered standard errors at the individual level (Womble and Hanemann, 2020). The extended structural specification is depicted in Equation (3.10):

$$G^{-1}(s_{ijt}) = \mu_j + \boldsymbol{\beta}_j \mathbf{X}_i + \boldsymbol{\gamma}_{1j} T_1 + \boldsymbol{\gamma}_{2j} T_2 + \boldsymbol{\gamma}_{3j} T_3 + \boldsymbol{\theta} R_t + \epsilon_{ijt} \tag{3.10}$$

Given randomization, estimating Equation (3.10) is equivalent to calculating treatment effects using a difference-in-differences approach. Figure 3.5 summarizes the results from the extended model. The APEs of policy interventions resemble earlier results

(Table S21). The APE of R_t is large and statistically significant, i.e. mere game repetition was associated with a 2.9 ha (4.4 ha) increase in area weeded with WR (SS) and a 7.3 ha decrease in area weeded with BC, a substantial reallocation. Potential explanations are discussed in Section 3.5.

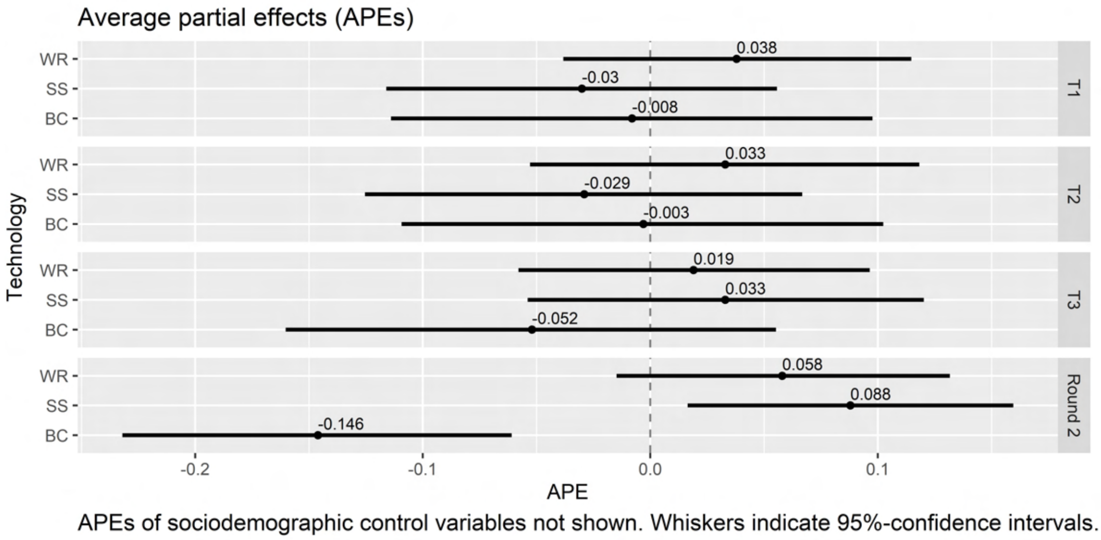

Figure 3.5: Treatment and round effects of technology allocation shares (pooled cross-sectional FMNL).

Note: T_1, subsidy; T_2, nudge; T_3, subsidy + nudge; *Round 2*, dummy for effect of second round; BC, broadcast application; SS, spot spraying; WR, weeding robot.

Furthermore, we explored the role of organic farming on weeding decisions (Table S22) by extending the model in Equation (3.8) with a dummy variable controlling for organic farming. On average, participants with an organic farming background allocated 6 ha (12 ha) more to SS (WR) than conventional farmers ($\text{APE}_{\text{organic}}$ SS: 0.121, 95 per cent CI [0.010, 0.232]; $\text{APE}_{\text{organic}}$ WR: 0.240, 95 per cent CI [0.165, 0.315]). Our results also show that attitudinal differences exist between conventional and organic farmers in our sample. Conventional farmers boasted relatively higher levels of innovativeness, explaining high receptiveness toward new yet familiar technologies, i.e. SS.

Organic farmers scored lower on innovativeness but higher on AttEnv compared to conventional farmers, which arguably motivated them to gravitate toward new SWT associated with yet unprecedented ways of sustainable farming. Additionally, we assessed potential heterogeneity of policy treatment effects by extending Equation

(3.9) with the organic farming dummy and interacting it with the treatment dummies (Table S23). The results suggest that organic farmers were more responsive to the policy treatments than conventional farmers (13.25 ha in response to the subsidy, $APE_{organic \times subsidy}$ WR: 0.265, 95 per cent CI [-0.005, 0.534] and 14.1 ha in response to the combined treatment, $APE_{organic \times (subsidy+nudge)}$ WR: 0.282, 95 per cent CI [0.012, 0.553]), indicating positive associations with a higher intention to use the WR in substantial economic and ecological magnitude. However, given the imbalance in our sample ($n_{organic}$ = 39, $n_{conventional}$ = 295), these explorative results must be interpreted with caution.

3.5 Discussion

This study focused on SWT as a technological alternative for German crop farmers using a lab-in-the-field experiment. Previous work suggests that farm-level adoption research must expand its focus to include behavioral factors in order to adequately depict the adoption process (Dessart et al., 2019; Hüttel et al., 2022). Correspondingly, we first studied the role of farmers' AttEnv, PI, and trust in farming data security and privacy as adoption determinants. SWT were explicitly framed to encapsulate novel technology characteristics, and relevant sociodemographic factors were controlled for. The baseline analysis showed that AttEnv and PI were positively associated with higher (lower) SWT (BC) adoption, yielding support for the corresponding hypotheses H1 and H2. Interestingly, higher adoption of WR was primarily associated with higher levels of AttEnv, while higher levels of SS, the intermediate and somewhat less innovative SWT, were primarily associated with higher levels of PI. Arguably, this finding was driven by attitudinal differences between the conventional and organic farmers in our sample, with the former scoring higher with respect to innovativeness and the latter revealing a higher AttEnv. We could not confirm previous research (e.g., Gabriel and Gandorfer, 2020; Jakku et al., 2019; Mohr and Kühl, 2021) reporting that farmers' (lack of) trust in the privacy of data collected by SFT is indicative of adoption intentions (H3). Except for Mohr and Kühl (2021), who base their findings on a small sample, in which 43 per cent of the subjects were non-farmers, our study is the first to conceptualize and quantify the effect of a data trust construct in this rigorous manner, which limits further comparison of our results with previous quantitative research. However, the insignificance of our finding may owe to the fact that young and educated managers of large farms are somewhat overrepresented in our sample vis-à-vis the average German farm population. Variation in attitudes toward security and privacy of farming data may thus not be sufficient to explain technology choices in the experiment. Nevertheless, in light of prevalent qualitative evidence, future studies should continue to develop an understanding of the circumstances in which concerns around farming data become relevant for technology adoption. The overarching message from the baseline results is that farmers with higher scores for environmental attitude and innovativeness were more willing to forego private returns to the benefit of society than participants who scored lower in these attitudinal constructs. Trust in farming data privacy, however, was not a relevant determinant of SWT adoption.

Our second objective was to assess policy scenarios to enhance farmers' adoption of societally desirable SWT. None of the treatments had a statistically significant effect on SFT adoption due to very heterogenous allocation shares. Specifically, the level of partial compensation and design of the green nudge seemed to be insufficient as an adoption incentive for this particular sample. Having acquired sufficient power via adequate sample size, we acknowledge that statistical insignificance of our results prevents the inference of conclusive treatment effects. However, in line with the ongoing debate on the use of p-values, we note that our findings may indicate quantitatively relevant effects that justify further exploration in adapted research designs (Heckelei et al., 2023). All policy effect estimates exhibited the expected sign, i.e. the subsidy (H4) and green nudge (H5) had a net positive association with the adoption of SWT. Notably, in both scenarios, this tendency was primarily driven by increased allocation to WR, whereas SS allocation shares dropped. The parameter estimates of the combined policy treatment (H6) were higher than those of the individual treatments. BC allocation dropped somewhat more, and SS and WR allocation were more balanced than under the single policy regimes. This is in line with our earlier line of argumentation. Farmers supposedly incorporate both personal and societal interests into their managerial decisions (Lynne et al., 2016) to simultaneously address personal and other interest. Similarly, to Czap et al. (2015) and Kuhfuss et al. (2016a), our findings may hint at the presence of such a combined policy effect. Interestingly, our results suggest organic farmers are more responsive to the policy treatments than conventional farmers. This finding is in line with the findings of a recent simulation-based study on SWT adoption in which Shang et al. (2023) found that organic farms are likely willing to pay substantially more for automated technology than conventional farms.

Some implications arise, nonetheless. Farmers showed a clear preference for broadcast allocation over SS over WR (Figure 3.2). While an overall preference for BC is expected given the higher hypothetical profit margin, the preference of SS over WR likely reflects varying degrees of familiarity and expertise with the respective technologies and AttEnv in our sample of farmers. Uncertainty associated with the novel characteristics of WRs, though not made explicit in our framing, may also have played a role. Overcoming the diverse potential barriers to SWT adoption may thus require a combination of technology maturation and carefully designed policy incentives. Along these lines, Rogers (2003) theorized that early adopters with an innovative, uncertainty-loving, and intellectual mindset can act as agents of change to initiate and subsequently accelerate the innovation process by being leading examples for their colleagues. Against this backdrop, Hüttel et al. (2022) found the impact of social norms driven by innovative peers and other technology users to be a major determinant of farmers' intention to use variable rate nitrogen application in crop farming. Similarly, Suvanto et al. (2020) showed that a higher entrepreneurial disposition, including low risk-aversion and innovativeness, was associated with a higher likelihood of starting the cultivation of sustainable protein-rich crops, and, finally, Blasch et al. (2022) looked at the adoption of precision farming tools in general to find that operators' higher innovativeness and openness toward eco-friendly farming practices were relevant predispositions to uptake. Our findings match this line of research, which justifies the suggestion that targeting innovative and pro-environmentally minded farmers would appear as a promising element in early dissemination strategies based on our findings.

We could not reject the null hypothesis related to H4–H6 after conducting our experiment, but this certainly does not imply that policy interventions do not matter for promoting the adoption of environmentally desirable SFT. All estimates of policy treatments, albeit statistically not significant, consistently pointed toward higher levels of WR adoption at a policy-relevant magnitude of up to 2.2 additional ha on a single hypothetical farm of 50 ha. In the German agricultural context, this is a relevant area to experiment with new technologies. If anything, the null result suggests that agricultural field robots, if not profitable from a purely private perspective, must come with policy interventions that at least compensate for opportunity cost and perceived additional downside risk (Finger, 2023). Green nudges alone, on the other hand, may not work to encourage adoption among all types of farm managers at this stage of technological development. Instead, as pro-environmental discourse becomes mainstream in the public sphere, the occasional scapegoating of agriculture may eventually lead to protest behavior with counterproductive responses to behavioral nudging attempts.

Some caveats apply. Although we could rule out randomization failures and control group contamination, participants in the control group ventured substantially more hectares into SWT in the second round than in the first round. We speculate that this round effect was driven by a combination of the hypothetical experimental setting and the perceived uncertainty associated with adopting a new technology (although not reflected in the actual fixed payoffs). After being reassured in the first round that payoffs materialized as promised, participants also became more familiar with the survey tool and eventually allocated more hectares to the less well-known technology options. Increased adoption may not only be indicative of gambling behavior but also reflect a subjectively perceived reduction in uncertainty. Our findings reveal the importance of including a control group in both baseline and treatment rounds to reduce the risk of overinterpreting treatment effects derived from uncontrolled before-and-after comparisons. Our results, however, are robust to excluding participants with extreme switching behavior. Round effects are caused by the order of the decision tasks within an experiment (Carlsson et al., 2012) and should thus have affected all participants in the same way in our experiment. Hence, our treatment effect estimates remain internally valid. Future work in this domain should pay careful attention to round effects by playing several rounds until stabilization of preferences is observed. We also acknowledge that the hypothetical nature and degree of abstraction created by reducing weed management to a simple area allocation may have confused or upset some participants, causing additional response heterogeneity or deviations from behavior in reality. We tried to address this aspect by making participation incentive-compatible and making payouts of vouchers and donations depend on decisions within the experiment. Moreover, our experiment depicted farmers' intended adoption at one particular point in time, making it difficult to differentiate between immediate and long-run adoption determinants. All these are known limitations of lab-in-the-field experiments (e.g., Thomas et al., 2019). As more SFT reach technological maturity, future adoption research would benefit from controlled and potentially longitudinal intervention studies in which some of these limitations can be addressed by conceptualizing adoption as a multidimensional process

(Khanna et al., 2022). This would enable insights into whether policy can have an influence on farmers' pro-environmental behavior and attitudes in the long run. While this has been shown for some types of human conservation behavior in general (Akerlof and Kennedy, 2013), no conclusive evidence exists for the agricultural context. Finally, the findings stem from a non-representative convenience sample and may therefore only apply to farmers with similar demographic and structural profile among which, however, early SWT adoption is most likely to be observed, rendering them a relevant subject pool to study.

3.6 Conclusion

The present study brings evidence from an economic experiment to the debate on adoption determinants of SFT, an emerging technology field with the potential to enable a sustainable agricultural transformation (King, 2017). In light of current medium to low adoption rates (Mizik, 2022), this debate is still largely based on assumptions and demonstration farm data and thus requires a systematic empirical foundation. Our study shows that German farmers' pro-environmental attitude and innovativeness seem to be relevant for the uptake and diffusion of SWT, indicating some willingness to forego private returns in favor of environmentally sustainable herbicide-efficient weeding options. However, data concerns, contrary to widely held concerns, seem to play a negligible role. The subsidy and the green nudge did not significantly affect SWT adoption, neither individually nor in combination, but the response to our treatments is positive on average and should be explored in future research. Thus, our findings inform the design of policy incentives required to accelerate the adoption of socially desirable agricultural innovations that may otherwise fail to unfold their full potential.

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Supplementary material

Supplementary data are available at *QOpen* online.

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Data availability

The data, R code and Online Appendix underlying this article are available in Centre for Open Science (OSF) at https://osf.io/nv8kp/?view_only=d1f3a00bd1e940b48b8c80b15e7cc4f8 in the respective folder named after the title of this paper.

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Chapter 4

Round effects in economic experiments– Insights from a business simulation game with agricultural students

Abstract: In their two-round framed lab-in-the-field experiment to evaluate, inter alia, the effect of hypothetical policies on German farmers' intended adoption of smart weeding technologies, Feisthauer et al. (2024) found that the behavior of the control group, although not having received a treatment, strongly resembled the treatment groups' behavior. They argue that this "round effect" may have been an important factor of rendering all policy effects statistically insignificant. We replicate the precursory study with German agricultural students in an adapted experimental design. We want to find out whether the round effect is a behavioral phenomenon specific to the farmer sample of the precursory study or whether it is a methodological issue inherent to multi-period experiments. Since we cannot reproduce a round effect but find a substantial policy treatment effect, our results point to marked differences between our student and the farmer sample. This stimulates the debate about subject pool effects and casts doubt on the adequacy of using students as a reference to study farmer behavior in agricultural policy evaluation experiments.

Keywords: Framed lab-in-the-field experiment, subject pool effects, replication study, policy evaluation, smart farming technologies

JEL classification: D91, B41, Q16

4.1 Introduction

In Chapter 3 in this dissertation, Feisthauer et al. (2024) conducted a framed lab-in-the-field experiment with German farmers to learn about their intentions to adopt smart farming technologies (SFT) for herbicide-reduced weed management. The authors designed a two-round business simulation game in which participants had to choose from several weeding technologies with different economic and environmental outcomes to conduct weed management on 50 hectares of hypothetical farmland. Specifically, farmers could choose a technology mix of broadcast application–relatively profitable but without environmental benefits–and two smart weeding technologies (SWT) with relatively lower profits but environmental benefits derived from hypothetical herbicide savings. The first round served as the baseline in which the authors assessed the statistical association of farmers' technology allocation shares with, inter alia, a set of attitudinal variables which were recorded prior to the game, namely pro-environmental attitude, personal innovativeness, and trust in the security and privacy of farming data. In the second round, the sample was randomized in four experimental groups. While the first group, the control group, played under identical experimental conditions as in round one, the treated groups received hypothetical policy scenarios that were hypothesized to have a positive effect on farmers' intention to use more sustainable SWT in the second round compared to the baseline.

The findings of the second round were surprising: The control group, although not having received a treatment, exhibited a change in technology allocation towards SWT in the sense of the hypotheses similar to the treated groups. This resulted in insignificant between-group differences in technology allocation in round two rendering the policy treatment effects indistinguishable from zero. An exploratory analysis–a pooled cross-sectional model including the allocation shares of both game rounds–further yielded a statistically significant coefficient for the "round two dummy". That is, merely playing a second round was associated with higher SWT allocation compared to the baseline. A within-group comparison of the treatment groups' weeding decisions across game rounds would have rendered all treatment effects statistically significant (cf. Thomas et al., 2019). Only the inclusion of a control group avoided this spurious interpretation.

Given the relative cost-efficiency of framed lab-in-the-field experiments (Gneezy and Imas, 2017) to test potential policies prior to their implementation, the discovery of what Feisthauer et al. (2024) coined "round effect" is arguably highly relevant from both a methodological and a policy perspective and thus motivates the present study. But based on the findings in Chapter 3 and in light of the paucity of similar studies in our field, it cannot be said whether the round effect is an inherent methodological issue of multi-period business simulation games or rather a peculiarity of the farmer sample collected in the above study. The objective of Chapter 4 is thus to attempt to answer this question and it therefore is to be read as a methodological addendum to Chapter 3. Consequently, we neither aim to derive further statements regarding the state of SFT adoption intentions among German crop farmers nor do we formulate additional policy recommendations to promote sustainable intensification of agriculture.

We replicate and adapt the experiment in Feisthauer et al. (2024) with German agricultural students. Thereby, our study does not only aim at increasing the awareness for potential round effects and hold as an orientation for future studies with similar experimental designs and samples. In comparing the results from the student sample to the farmer sample in Chapter 3, we also add to the debate about subject pool effects, i.e., we discuss the question whether agricultural students can hold as an adequate reference to study the behavior of professional experimental subjects, e.g., farmers (Peth and Mußhoff, 2020).

In the remainder of this chapter, we first outline the adapted experimental design, the analytical approach and the composition of the student sample (Section 4.2). This is followed by the presentation of descriptive and multivariate analysis results (Section 4.3). Finally, we discuss the results and conclude by pointing out implications for future research (Section 4.4).

4.2 Methods and data

4.2.1 Experimental design

We largely retained the framing (playing the role of a crop farmer), design (50 hectares of farm land, 3 weeding technologies with original attributes) and the choice task (choose weeding technology mix for each round) of the precursory lab-in-the-field experiment in Feisthauer et al. (2024) as show in Table 4.1.

Table 4.1: Description of weeding technologies.

	Broadcast application	**Spot spraying**	**Weeding robot**
Steering mode	Tractor with human driver	Tractor with human driver	Autonomous
Profit margin (pts/ha)	90	66	66
Ecological value (pts/ha)	0	45	45

Regarding the length of the experiment and the treatments, we made several changes in line with the objective outlined in Section 4.1. First, to the track with two game rounds–baseline and one treatment round–we added a second track playing four game rounds–baseline and three treatment rounds. This design change was motivated based on the consideration that the round effect, given its presence, might change in magnitude as the game progresses (Day et al., 2012). Second, for parsimony, we only retained one policy scenario which was shown to the treatment groups in both the two-round and the four-round track. That is, respective participants would receive a subsidy of ten points for each hectare on which they chose a SWT for weed management. Table 4.2 depicts the adapted course of the experiment for each group.

Table 4.2: Flow of experiment and randomized assignment to treatment groups.

	Round			
Treatment	**1**	**2**	**3**	**4**
Subsidy = 0	Baseline	Group 1	-	-
	Baseline	Group 3	Group 3	Group 3
Subsidy = 1	Baseline	Group 2	-	-
	Baseline	Group 4	Group 4	Group 4

Furthermore, the same formulae to calculate private profit, ecological value, and societal utility were presented to participants before each game round. Specifically, Equations (4.1), (4.3) and (4.4) were shown to all participants in the baseline and to those who were assigned to a control group in subsequent rounds (group one or group three). Treated participants in groups two and four saw Equations (4.2), (4.3) and (4.4) in subsequent rounds after the baseline.

$$Private\ profit_{(baseline;subsidy=0)} = 90 \times \mathrm{ha}_{\mathrm{BC}} + 66 \times \mathrm{ha}_{\mathrm{SS}} + 66 \times \mathrm{ha}_{\mathrm{WR}} \tag{4.1}$$

$$Private\ profit_{(subsidy=1)} = 90 \times \mathrm{ha}_{\mathrm{BC}} + 66 \times \mathrm{ha}_{\mathrm{SS}} + 66 \times \mathrm{ha}_{\mathrm{WR}} + 10 \times (\mathrm{ha}_{\mathrm{SS}} + \mathrm{ha}_{\mathrm{WR}}) \tag{4.2}$$

$$\text{with} : \mathrm{ha}_{\mathrm{BC}} + \mathrm{ha}_{\mathrm{SS}} + \mathrm{ha}_{\mathrm{WR}} = 50\ \mathrm{ha}$$

$$Ecological\ value = 45 \times \mathrm{ha}_{\mathrm{SS}} + 45 \times \mathrm{ha}_{\mathrm{WR}}, \tag{4.3}$$

$$Total\ societal\ utility = private\ profit + ecological\ value. \tag{4.4}$$

As in the precursory study, we asked participants to express their attitudes towards the environment, towards innovations, and towards the security and privacy of farming data via a set of 7-point Likert scale questions. At the end of the survey, participants were asked to respond to a set of questions regarding their sociodemographic background (see Supplementary Information for the list of all recorded variables).

Finally, this replication experiment with agricultural students was incentivized, as well, as this is said to increase truthful response behavior and samples size (Göritz, 2006). Participants were informed that their ecological value achieved in one randomly selected game round would be converted into a donation to a German environmental agency at a game point to Euros exchange rate of 300 to 1. Moreover, they could insert their email address to redeem the countervalue of their private profit from the same randomly selected game round and it consisted of an online voucher code for an electronics and technology retailer. Voucher values and donations could range from 11 Euros (show-up fee) to 15 Euros and from 0 Euros to 7.50 Euros, respectively.

4.2.2 Analysis

The outlined extended lab-in-the-field experiment was part of a larger study within our research group to study the nature of round effects in multi-period stated preference experiments in more depth. Please refer to Leyens et al. (2024) who apply an alternative theoretical and methodological perspective to the full data set collected in this endeavor. Although our primary focus remains with round effects, too, the objective of the present chapter, however, is to replicate the identical experimental conditions in Feisthauer et al. (2024) and compare their results to the findings of our student sample. For commensurability, we thus draw on the same analytical procedures of the precursory study. Furthermore, although the sample description in Section 4.2.3 below depicts the full sample, all results and the discussion in Section 4.3 and Section 4.4, respectively, are derived from a subsample including only participants in group one and group two who played two game rounds (Table 4.2).

We use the same fractional multinomial logit (FMNL) procedure as in Feisthauer et al. (2024). The baseline is analyzed according to Equation (4.5), in which s_{ij} represents the technology allocation share of student *i* to technology *j*. Additionally, μ_j represents the technology-specific intercept, $\boldsymbol{\beta}_j$ is the technology specific parameter vector and $\boldsymbol{X}_i$ is a matrix of student characteristics including the variables of main interest of the baseline analysis - the attitudinal constructs. The error term is given by ϵ_{ij}.

$$G^{-1}(s_{ij}) = \mu_j + \boldsymbol{\beta}_j \mathbf{X}_i + \epsilon_{ij} \tag{4.5}$$

The FMNL model specification for the treatment round assessment is given by Equation (4.6) in which the coefficient of the subsidy policy scenario T on the allocation shares of each technology *j* is represented by γ_j.

$$G^{-1}(s_{ij}) = \mu_j + \boldsymbol{\beta}_j \mathbf{X}_i + \boldsymbol{\gamma}_j T + \epsilon_{ij} \tag{4.6}$$

Similarly, the pooled cross-sectional model specification for game rounds one and two which includes the coefficient θ for the round effect R_t is given by Equation (4.7).

$$G^{-1}(s_{ijt}) = \mu_j + \boldsymbol{\beta}_j \mathbf{X}_i + \boldsymbol{\gamma}_j T + \boldsymbol{\theta} R_t + \epsilon_{ijt} \tag{4.7}$$

4.2.3 Data

Data were collected in November and December 2022.[16] The online survey was distributed via email through multiple channels within the authors' networks to agricultural students from German universities, technical colleges and vocational schools. In total, 403 students clicked on the link to begin the survey of which only 277 completed it (dropouts n=126, dropout rate=31.3%). Furthermore, we excluded participants who

[16] Since data collection was part of the joint endeavor within our research group, this section is, in a large part, taken from Leyens et al. (2024). We received explicit permission of the authors to reproduce it here and adapt details in line with the objective of the present chapter, where needed.

did not consent to the use of their anonymized experimental responses (n=2), those who indicated they were no students (n=8), and those who answered a test question regarding the experimental instructions incorrectly (n=64) which yielded the final data set of 203 usable observations (Table 4.3). Among all usable survey submissions, the average participation duration across all groups was 37.1 minutes. The voucher and environmental donation payouts averaged to 13.0 and 4.5 Euros, respectively. The average participant's age was 22.7 years and the sample was approximately composed of 55.0% male and 45.0% female student. While about half of the sample did not have any prior practical farming experience, 22.7% were accustomed to working on their family business, 14.8% had several years of experience and 14.3% had completed an internship. A large majority of participants were university students (83.0%), while the remainder were enrolled in technical colleges (13.0%) and vocational schools (3.9%).

Table 4.3: Sociodemographic characteristics of the full sample.

Variable	**Mean(SD), count(share)**[b]
Age in years	22.7 (2.7)
Gender	111 (55.0%) male
	91 (45.0%) female
	1 (0.5%) diverse
Prior farming experience	98 (48.3%) no experience
	46 (22.7%) work experience on family farm
	30 (14.8%) several years
	29 (14.3%) completed an internship
Type of educational institution	169 (83.0%) university
	26 (13.0%) technical college
	8 (3.9%) vocational school
Experience/knowledge of SFT (yes/no)	102 (50.0%)
Pro-environmental attitude[a]	5.9 (1.0)
Personal innovativeness[a]	4.8 (1.4)
Trust in security and privacy of farming data[a]	4.1 (1.2)

n = 203
[a] 7-point Likert scale multi-item construct to evaluate participants' self-rated fatigue during the survey. See Supplementary Information for details.
[b] Percentages are rounded to one decimal point and thus do not necessarily add up to 100%.

Exactly half of the sample (50.0%) had prior experience or (and) knowledge of smart farming technologies (SFT). Lastly, regarding the attitudinal measures, participants had a high average level of pro-environmental attitude (mean=5.9) while expressing moderately high levels of personal innovativeness (mean=4.8) and trust in the security and privacy of farming data (mean=4.1).

4.3 Results

In the following, we first elaborate on the descriptive results of the weeding technology allocation shares (Section 4.3.1) which is followed by the presentation of the multivariate analysis (Section 4.3.2). Please note that we will focus only on the results of groups one and two which played two game rounds (n=108). Details on game outcomes for the full sample are compiled in Tables S3 and S4 in the Supplementary Information. Yet, prior to the subsample analysis and for completeness, we conducted a balance test which yielded no statistically significant differences in any sociodemographic variable, i.e., randomization of the experimental groups was successful (see Table S1 in Supplementary Information for details).

4.3.1 Descriptive analysis

In the baseline, a preference of broadcast application over spot spraying over the weeding robot is present in both groups (Figure 4.1). A pairwise Mann-Whitney-U-test yielded no statistically significant differences in area allocation between groups (Table S5). To this point, the results of the student subsample strongly resemble the farmer sample in Feisthauer et al. (2024).

In going from round one to round two, we observe negligible changes in technology allocations in the control group (<1 hectares). This is confirmed by an insignificant Wilcoxon rank sum tests of within-group differences (Table S6). By contrast, the treatment group reduces broadcast application allocation by 4.40 hectares and increases spot spraying and weeding robot by 2.00 and 2.40 hectares, respectively (Table 4.4).

The Wilcoxon rank sum tests shown in Table S6 renders these within-group differences statistically (marginally) significant for broadcast applications and the weeding robot (spot spraying). In absolute terms, the area assignments of the control group differ from the treated group by 5.30 hectares, -5.80 hectares, and 0.50 hectares for broadcast application, spot spraying, and the weeding robot respectively (Figure 4.1). In other words, in round two, the control group allocates substantially more (less) area to broadcast (spot spraying), as indicated by marginally significant pairwise Mann-Whitney-U-test results of between-group differences (Table S5).

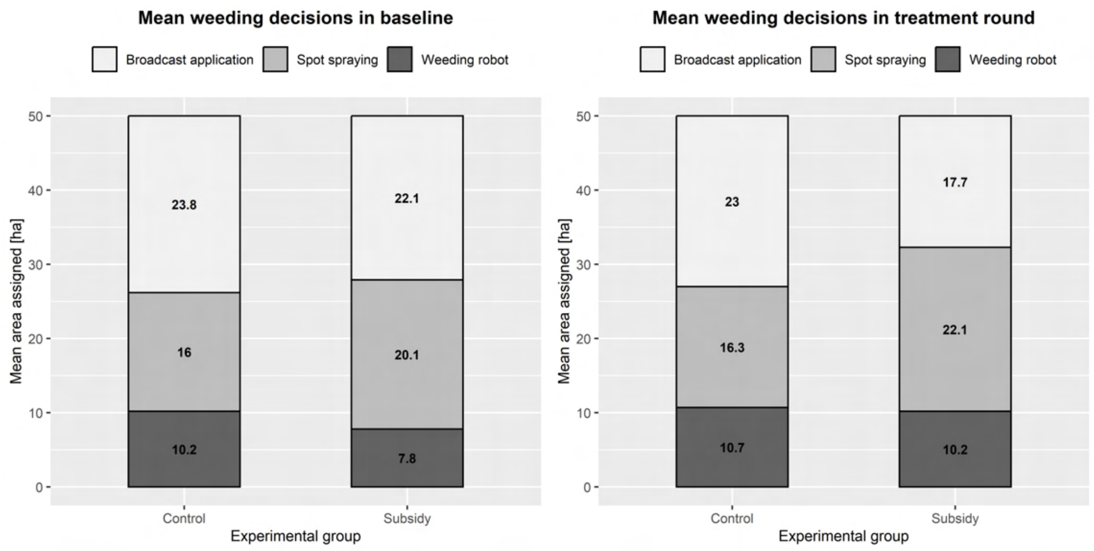

Figure 4.1: Mean weeding decisions in baseline and treatment round.

Finally, a pairwise Mann-Whitney-U-test of difference in changes of weeding technology allocation from round one to round two underlines the above by yielding (marginally) significant group difference regarding allocation changes in hectares for broadcast application (weeding robot) (Table 4.4).

Table 4.4: Average change of weeding technology allocation from round one to round two and test of differences.

	Technology allocation change in hectares, mean (SD)		
Technology	**Control group**	**Subsidy group**	**p-value**[a]
Broadcast application	-0.8 (12.2)	-4.4 (8.3)	0.029
Spot spraying	0.3 (10.9)	2.0 (7.5)	0.330
Weeding robot	0.5 (7.8)	2.4 (4.6)	0.095

[a] Pairwise Mann-Whitney-U-test of differences between experimental groups.

These descriptive results suggest a statistically detectable reaction of group two to the subsidy treatment. Furthermore, seeing that the control group exhibits similar area allocation in both rounds hints to the absence of a round effect in this group. These findings are in sharp contrast to Feisthauer et al. (2024). However, looking at the baseline group differences in weeding robot allocation, it may be plausible that part of the reaction to the treatment of group two may have been due to 'catching up'. This assumption is enhanced when comparing the baseline weeding robot allocation of all four groups (Table S4)–group two has the lowest initial allocation to weeding robot. But seeing that group two increases not only the weeding robot but also the spot spraying area in round two strengthens the case of an effectual subsidy treatment again.

4.3.2 Multivariate analysis

We now turn to the results of the multivariate analyses. The effect size plots below (Figures 4.2 to 4.4) only depict the variables of interest of the respective analyses (attitudinal constructs, policy treatment, round effect). Additional covariates, although included in each model estimation, are not presented in the main body of the text. Regarding several sociodemographic control variables, the student sample turned out rather homogenous and the majority thereof were strongly imbalanced, e.g., 'type of educational institution'. We therefore decided to drop these variables from the regressions. We further decided to drop the variables 'age' and 'gender' due to low variability and arguably low information value, respectively. The retained control variables were 'experience/familiarity with smart farming technologies' and 'prior farming experience'. For model parsimony, the latter variable was transformed into a binary variable with 0 representing 'no experience/completed internship for study program' and 1 representing 'several years of experience/works on family farm'. As in the precursory study, attitudinal constructs entered the analyses as standardized mean scores. Please refer to Tables S7 to S9 in the Supplementary Information for numeric model results in tabular form.

The analysis results of pre-treatment SWT adoption determinants are shown in Figure 4.2 and Table S7. A one-standard deviation increase in pro-environmental attitude is significantly associated with a 6.1% (3.05 hectares) increase in area allocated to the weeding robot. A one-standard deviation increase in personal innovativeness is statistically significantly associated with a 13.9% (6.95 hectares) decrease in spot spraying allocation area and a 18.4% (9.20 hectares) increase in area allocated to broadcast application. Finally, an increase of trust in the security and privacy of farming data is significantly associated with a 7.2% (3.60 hectares) reduction in area allocated to the weeding robot and an increase in area allocated to broadcast application by

11.3% (5.65 hectares). The baseline results of the farmer sample in Feisthauer et al. (2024) and our student subsample resemble each other regarding pro-environmental attitude. The results for personal innovativeness and data trust, however, contrast each other. That is, for personal innovativeness we find the opposite signs with (marginal) significance for all three technologies. A similar pattern arises for data trust–finding significant average partial effects (APEs) for the weeding robot and broadcast application at relevant magnitudes is a novel observation compared to the farmer sample. On a more general note, most APEs seem to be larger in magnitude in the present case compared to Feisthauer et al. (2024).

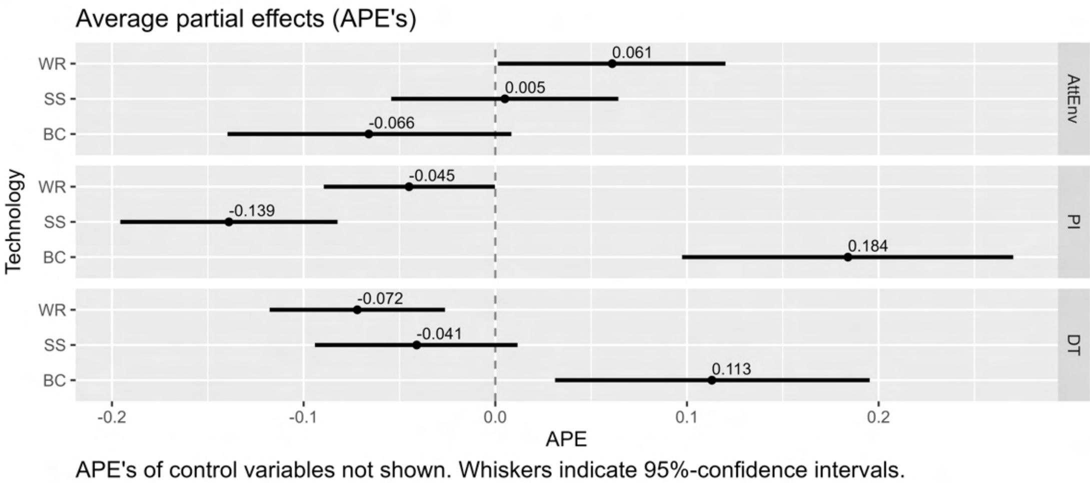

Figure 4.2: Baseline determinants of technology allocation shares (FMNL).

The results of the treatment round analysis are shown in Figure 4.3. Minor changes in the magnitudes of the APEs of the attitudinal constructs notwithstanding, the results of the baseline remain by and large robust (detailed results are given in Table S8). The results for the subsidy treatment are promising. Having received the subsidy in round two, is significantly associated with an increased area allocation to spot spraying by 24.3% (12.15 hectares) and a 28.8% (14.40 hectares) reduced allocation to broadband application. This multivariate finding underscores the descriptive analysis in Section 3.1. regarding a notable treatment effect. Clearly, this is a stronger finding than in the precursory study in which no statistically significant treatment effect with comparable magnitude and direction was found.

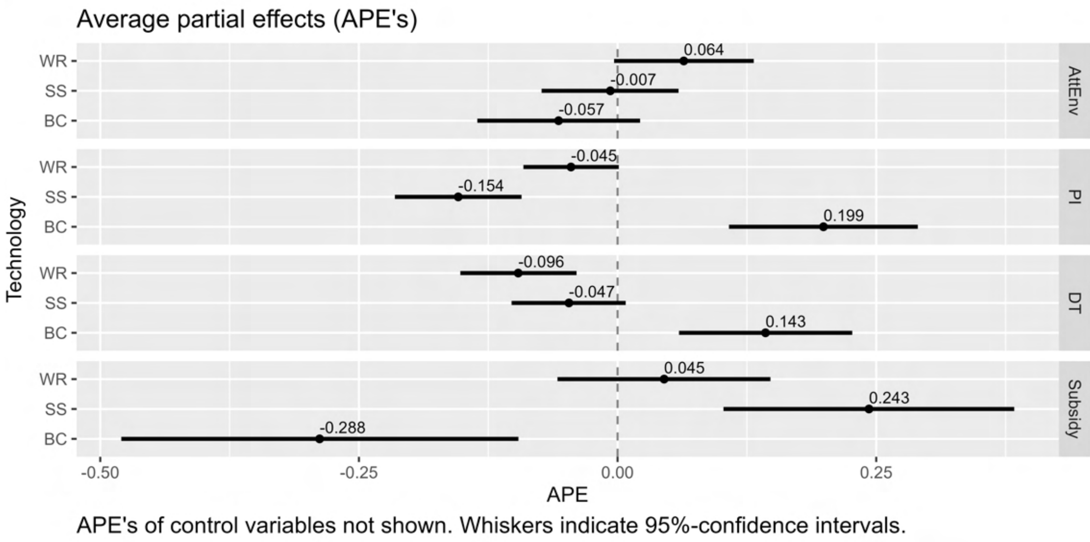

Figure 4.3: Treatment round determinants of technology allocation shares (FMNL).

Note: BC, broadcast application; SS, spot spraying; WR, weeding robot; AttEnv, pro-environmental attitude; PI, personal innovativeness; DT, trust in security and sovereignty of farming data; Subsidy, subsidy policy treatment dummy

In a last step, we present the results of the pooled cross-sectional analysis including observations of both round for groups one and two (Figure 4.4).

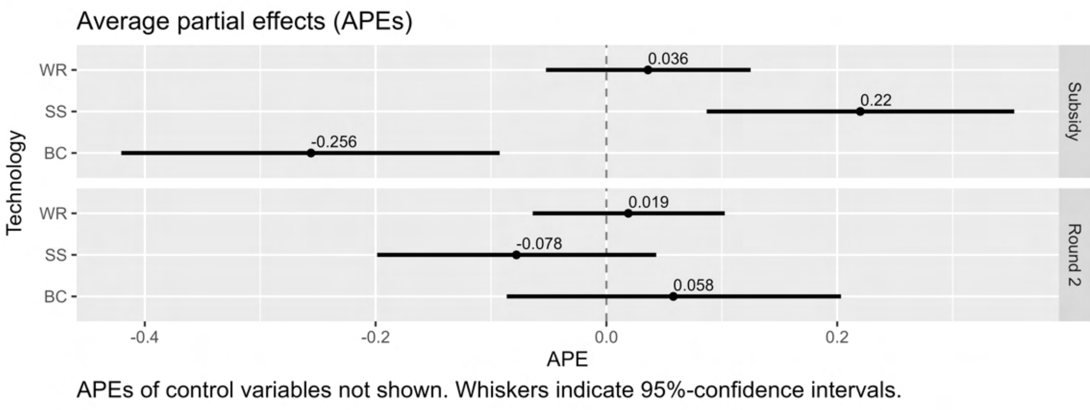

Figure 4.4: Treatment and round effects of technology allocation shares (pooled cross-sectional FMNL).

Note: Subsidy, subsidy policy treatment dummy; Round 2, round effect dummy

As before, the results of the attitudinal variables (not shown) next to the subsidy treatment effect are by and large reproduced in this model (detailed results are shown in Table S9). Seeing that the confidence intervals of the APEs of the dummy controlling for round two clearly include the zero suggest that there is no statistically significant round effect. This strongly contrasts the findings in Feisthauer et al. (2024) who find a statistically significant and negative (positive) APE for the round effect on broadcast application (spot spraying).

4.4 Discussion and conclusion

The primary aim of this chapter was to replicate the experiment in Feisthauer et al. (2024) with an adapted design to find out whether the round effect in the precursory study could be reproduced. This would then indicate a methodological flaw inherent to multi-period business simulation games. While the related phenomenon of ordering effects in stated preferences methods with repeated choice tasks has extensively been recognized in consumer behavior literature (e.g., Day et al., 2012), we are not aware of any mention in comparable references in our field of experimental agricultural economics (e.g., Blasch et al., 2022; Fleming et al., 2021; Musshoff and Hirschauer, 2014; Thomas et al., 2019). However, experimental designs which do not account for round effects are at risk of contorting participant behavior, lead to over- or underestimation of experimental treatment effects and eventually yield false conclusions regarding societally and economically highly relevant policies (Feisthauer et al., 2024; Thomas et al., 2019). The awareness of and methodological measures to account for round effects should thus be a high priority in any future study. The inclusion of a control group enabled the identification and discussion of round effects in both of the discussed studies and we urge scholars to retain control groups as indispensable elements in any future multi-period experiment. Further methodological advancements are clearly required to understand the deeper nature of round effects (Leyens et al., 2024).

The results of the present replication study with agricultural students do not suggest a round effect. Seeing that the estimations of the behavioral constructs and the treatment effect remain robust, once we control for a potential round effect, indicates that the temporal design of the survey does not cause substantial bias of the results. In consequence, we may assume that the round effect may indeed have been a behavioral peculiarity of the farmer sample collected in the previous study. Feisthauer et al. (2024)

state that their non-representative convenience sample was marked by young, especially innovative, and well educated farmers among which a certain degree of digital literacy and familiarity with answering surveys in an online format could have been expected. However, their observations suggest otherwise. The concept of institutional learning postulates that experimental subjects oftentimes need to familiarize themselves with the experimental setting and the complexity of choice tasks which is associated with substantial deviations in respondents' behavior, especially, in early phases of a survey (Chou et al., 2009; Day et al., 2012). This may be an alternative explanations for what was observed in the precursory study but it does, however, not apply to our student sample. Arguably, the students were even more experienced with participating in online surveys which allowed them to understand the experimental instructions and trust the voucher payout structures from the outset.

In the same vein as Peth and Mußhoff (2020), we also compare the farmer sample to our student subsample on a more general level. Without interpreting our findings regarding the attitudinal measures and the subsidy treatment in particular depth, substantial sample differences regarding the magnitude, significance and direction of the APEs of most variables of interest shall be highlighted. This casts doubt on the extent to which student samples can reliably be used to derive assumptions regarding the behavior of farmers in our context. Given the scarcity of studies which assess attitudinal and behavioral differences between students and farmers and seeing that our finding of marked differences between the student and farmer sample somewhat contrasts Peth and Mußhoff (2020) and the reviewed literature therein, caution is clearly warranted for the interpretation of policy evaluation experiments with non-professional subject pools. While student samples are cheaper to acquire and more readily accessible (Harrison and List, 2004), we argue that with increasing degree of contextualization of experiments, comparability of student and farmer samples declines. Our results not only point to a difference between students' and farmers' responsiveness to a hypothetical subsidy for smart weeding technologies but we also observe a fundamental difference in subjects' behaviors in relation the game round played. We therefore recommend to continue to conduct framed policy evaluation experiments with potential beneficiaries.

Acknowledgments

This work was part of a larger project to not only replicate but extend the analysis of round effects in agricultural economic experiments as recommended in Feisthauer et al. (2024). The experimental conceptualization and data collection was a joint endeavor within our research group and I would thus like to acknowledge the invaluable contributions of Alexa Leyens, Jan Börner and Monika Hartmann in this process. Information regarding parts of this collective procedure, i.e., the adapted experimental design, descriptive sample statistics and the data collection procedure have been outlined in Leyens et al. (2024) and are, with explicit permission of the authors, reproduced here and adapted in line with the objective of the present chapter, where needed.

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Compliance with ethical standards

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

Data availability

The data to this chapter is available on OSF via this link: https://osf.io/mn6gc/?view_only=963da5fb0ee94f8f8889a012ce66151c. The R code is available upon request with the author.

Supplementary Information

Supplementary Information to this chapter is available on OSF via this link: https://osf.io/mn6gc/?view_only=963da5fb0ee94f8f8889a012ce66151c.

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Chapter 5

Behavioral factors driving farmers' intentions to adopt spot spraying for sustainable weed control[17]

Abstract: Smart Farming Technologies enable plant-specific agrochemical applications which can increase the efficiency and reduce the environmental impacts of agriculture. However, the uptake of Smart Farming Technologies remains slow despite their potential to enhance sustainable transformation of food systems. The design of policies to promote sustainable agricultural technologies requires a holistic understanding of the complex set of factors driving the adoption of innovations at farm level. This study has a focus on behavioral factors, such as pro-environmental attitude, personal innovativeness and moral norms. Based on an online study conducted in Germany, structural equation modelling is applied to test the predictions of an extended version of the Theory of Planned Behavior, using spot spraying, a smart weeding technology, as an example. The results confirm theoretical predictions and show that indicators of attitude, subjective norms, and perceived behavioral control have relevant effects on farmers' adoption intentions. The extended model revealed a medium-sized (small) direct effect of moral norms on the attitude towards spot spraying (adoption intention). Personal innovativeness had a small effect on adoption intention, whereas pro-environmental attitude did not exhibit a clear direction of impact. Methodological and policy implications derived from the results are discussed noting that the inclusion of indicators for moral norms can improve the predictive power of models used in future research in this field. Overall, initiatives aimed at facilitating the exchange of opinions and related moral norms as

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well as collaboration among peers may contribute to voluntary sustainable innovation as it enhances adoption intentions among farmers.

Keywords: Smart farming technologies, Sustainable intensification, Partial least squares structural equation modelling, Voluntary technology uptake, Agricultural policy

JEL classification: Q16, Q18, D91

5.1 Introduction

In order to meet the rising global food demand (von Braun et al., 2021), agricultural productivity growth of the last few decades was predominantly achieved through intensified cultivation of cropland via, e.g., increased use of pesticides and fertilizers. This development, however, is associated with biodiversity loss and threats to ecosystem stability (Newbold et al., 2015). Agricultural policy makers, especially in the developed world, have recognized and started to address the potentially harmful effects of excessive agrochemical application to human and environmental health. Against this backdrop, the European Union's Farm to Fork strategy–a multi-annual agenda towards more resilient, sustainable, safe and accessible food production–seeks to reduce the use of pesticides by 50% in all member states until 2030 (European Union, 2020).

Technological innovations in general (Springmann et al., 2018) and Smart Farming Technologies (SFT) in particular are considered key elements to enable the shift towards sustainable intensification and thus more eco-efficient ways of farming (Finger et al., 2019; Garnett et al., 2013; Rübcke von Veltheim et al., 2019; Walter et al., 2017). As opposed to uniform field operations, SFT allow for plant-specific treatment which implies several advantages throughout the production process. Precision application of chemicals reduces runoff to the environment (Aubert et al., 2012; Wolfert et al., 2017), is associated with lower agricultural greenhouse gas emissions (Balafoutis et al., 2017) and, with growing maturity of SFT, it may even be economically beneficial for farmers due to savings in fuel, chemical and manual labor inputs (Balafoutis et al., 2017; Lowenberg-DeBoer et al., 2020; Weersink et al., 2018). Nevertheless, adoption rates of digital innovations among farmers are currently low (Aubert et al., 2012; Barnes et al., 2019; Paustian and Theuvsen, 2017). Marketing and policy strategies to promote uptake and diffusion could thus enable SFT to unfold their substantial environmental potential. The design and implementation of such strategies, however, requires a more in-depth understanding of the underlying factors that drive farmers' attitudes and motives regarding SFT. Among these factors, the understanding of behavioral determinants of agricultural technology adoption still remains limited (Thompson et al., 2023). This study thus takes a behavioral perspective to investigate adoption intentions of spot spraying, a sensor-based smart weeding technology (SWT) for precision herbicide application in crop farming.[18]

Over the past decades, substantial research on adoption determinants of sustainable and digital farming technologies has been conducted with a primary focus on observable farmer and farm-level characteristics, i.e., sociodemographic and structural aspects such as age, gender, education level, farm size or biophysical parameters (e.g., Barnes et al., 2019; Groher et al., 2020; Michels et al., 2020b). Depending on, e.g., study design and context, sampling and estimation strategy, or technology investigated, results vary. Similarly, review studies aiming to integrate previous findings yield inconclusive results (e.g., de Oca Munguia and Llewellyn, 2020; Pathak et al., 2019; Pierpaoli et al., 2013; Tey and Brindal, 2012). Furthermore, the literature on adoption of sustainable farming technologies has been criticized as so far only few studies considered behavioral and normative factors (Dessart et al., 2019). Those behavioral studies applied different theoretical frameworks. Using the Reasoned Action Approach, Hüttel et al. (2022) find that social norms were the single most important determinant of farmers' intentions to use a precision nitrogen application technology. By contrast, in a study on the acceptance of artificial intelligence technology in agriculture (Mohr and Kühl, 2021), the TPB and the Technology Acceptance Model were combined to find that farmers' personal attitude and perceived behavioral control were most relevant in explaining acceptance whereas subjective norms appeared irrelevant. To study the use of agricultural smart phone apps, Michels et al. (2020b) adapted the Unified Theory of Acceptance and Use of Technology. They found that two attitudinal determinants, namely effort and performance expectancy, next to subjective norms were most relevant in explaining behavioral intentions. By comparison, Aubert et al. (2012) combined the Technology Acceptance Model with the Diffusion of Innovations Theory to simultaneously assess the role of behavioral

[18]Spot spraying is a plant protection technology for high-precision agrochemical application. High-resolution AI-supported cameras are attached to the spraying boom mounted to or pulled by a tractor to recognize and differentiate weeds from crop plants. Subsequently, the nozzles can be operated individually to apply herbicides to single weed plants only and thus allowing for substantial herbicide reductions.

aspects and technology attributes for the adoption of multiple precision agriculture tools. Besides the ease of use, perceived usefulness and farmers' self-rated innovativeness, they found perceived resources to be important adoption determinants. Lastly, Beza et al. (2018) applied an extended Unified Theory of Acceptance and Use of Technology to study the use intentions of SMS services for farming data collection and identified that expected effort, performance and profitability, along with farmers' trust in the service were significant positive determinants of behavioral intention.

This paper adds a theory-driven empirical analysis to the literature by testing the suitability of the Theory of Planned Behavior (TPB) (Ajzen, 1991) for investigating spot spraying adoption intentions for sustainable weed management. Furthermore, we investigate the relevance of extending the TPB by environmental and moral norms as additional drivers of sustainable innovation uptake allowing for an in-depth understanding of the drivers of German farmers' adoption intentions and potential antecedents of the attitude towards this technology.

The findings of this study have implications for future research and policy alike as they highlight the strength of subjective and moral norms for the adoption intention and the attitude towards spot spraying, respectively. Considering the increasing emphasis of the European Union's Common Agricultural Policy to develop a more diversified policy landscape to promote voluntary uptake of sustainable farming practices and technologies (European Commission, 2019), the presented insights reveal the relevance of farmers' awareness of the relative advantageousness of spot spraying which thus hints at the importance of social exchange and collaboration among farmers. Local policy schemes which enable communication and exposure to the attitudes and moral compass of colleagues may heighten farmers' attitudes towards SFT, address causes of current restraints and potentially facilitate the initial access to smart innovations. Eventually, this may be a more cost-efficient way to accelerate the diffusion of environmentally and societally conducive SFT towards sustainable intensification in modern farming (Dessart et al., 2019). The remainder of this paper is structured as follows. In the next section, the research hypotheses based on the TPB and the extension of the framework are derived. This is followed by the description of the survey design and sample statistics. Subsequently, the results are presented and discussed. The article concludes with a discussion of the limitations and an outlook for future research.

5.2 Theoretical framework

The Theory of Planned Behavior (TPB) (Ajzen, 1991) is a psychological framework that draws on three behavioral constructs–attitude, subjective norms and perceived behavioral control–to predict subjects' intention to pursue a specific behavior. Attitude represents the degree to which the individual perceives this behavior as desirable, beneficial or useful. Subjective norms refer to social influences or pressures affecting the individual regarding (not) performing the given behavior. Lastly, perceived behavioral control represents an individual's own perceived capabilities and control to perform the focal action. More favorable attitudes, subjective norms and perceived control over the behavior are assumed to lead to a higher intention towards the behavior in question. Hence, the following three hypotheses are formulated:

> **H1.** A favorable attitude towards using spot spraying has a positive effect on the intention to use spot spraying for weed management.
>
> **H2.** Subjective norms that are in favor of using spot spraying have a positive effect on the intention to use spot spraying for weed management.
>
> **H3.** A high level of perceived behavioral control with respect to using spot spraying has a positive effect on the intention to use spot spraying for weed management.

The TPB has frequently been applied to the context of sustainable agricultural innovations and practices (Sok et al., 2021). In a number of cases the TPB has been extended to more adequately capture the decision context of the behavior under consideration (Sniehotta et al., 2014), as suggested by Fishbein and Ajzen (2010). In this study, the conceptual framework is extended by three constructs potentially relevant for explaining farmers' intention to use spot spraying.

According to Rogers' (2003) seminal Theory of Diffusion of Innovations, individuals who try and implement innovations at early stages are described as venturous, uncertainty-loving, and keen to gather information on latest technological gadgets which, if evaluated positively, results in a positive attitude towards a particular innovation. Several studies on digital farming technology adoption have used the concept of farmers' innovativeness as an explanatory behavioral measure in different conceptual setups. For example, Michels et al. (2020b) and Aubert et al. (2012) found a small but positive direct effect of farmers' innovativeness and smart phone ownership, respectively, on adoption of precision farming tools. However, a significant effect of personal innovativeness could not be confirmed in Beza et al. (2018) for the case of farmers' intention to use SMS for agricultural services. Finally, Barnes et al. (2019) found innovativeness to be a significant determinant for variable rate nitrogen fertilizer technology adoption only for those farmers who had previously adopted a machine guidance technology. The notion of an immediate impact of innovativeness on intended adoption behavior may, however, disregard an important intermediate step. Specifically, farmers with higher levels of innovativeness may demonstrate higher interest and effort to gather information regarding technological characteristics and in-field performance (Aubert et al., 2012), be more motivated to actively seek out advice from colleagues and increase their exposure to demonstrations and information regarding technological developments (Blasch et al., 2022; Reichardt and Jürgens, 2009). This could enable practitioners to develop a more substantiated perception of particular innovations which will, eventually, allow them to form a well-informed and more determined adoption intention (Aubert et al., 2012), assuming the innovation at hand was positively evaluated (Reichardt and Jürgens, 2009). This suggests an indirect pathway of farmers' willingness to learn and try out SFT on intended adoption via favorable attitudes towards the innovation. Along these lines, Mohr and Kühl (2021) find use attitudes and control believes to mediate the effect of personal innovativeness on farmers' acceptance of agricultural AI technologies. Accordingly, hypothesis four is formulated:

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

The TPB captures the effect of subjective norms on individuals' intentions while personal values, e.g., environmental concerns and moral norms are not explicitly considered (Ajzen, 1991). Dessart et al. (2019) postulate that environmental concern is a dispositional behavioral determinant manifesting in all of a farmer's decisions. Potential environmental consequences of future decisions are evaluated accordingly, such that for farmers with high pro-environmental values, actions in favor of the environment create a satisfactory feeling, while pursuing actions harming the environment might induce a feeling of guilt (Andreoni, 1990) and cognitive dissonance (Festinger, 2009). Previous studies assessing the relevance of farmers' environmental concerns for their adoption frequently focused on organic farming. For example, Toma and Mathijs (2007) found environmental concern to be a direct antecedent of Romanian farmers' willingness to participate in organic farming programs. Moreover, Läpple (2010) assessed the timing of Irish farmers' organic farming adoption and showed that higher environmental concerns were a relevant predictor of adoption for early as well as late adopters. However, a high level of a general pro-environmental attitude may not necessarily manifest in higher inclination towards respective behaviors (Bamberg et al., 1999; Best, 2010). Specifically, pro-environmental attitude may have an indirect effect on intended adoption through a more positive attitude towards specific sustainable practices or innovations. For the case of energy-efficient vehicle adoption intention in China, Wang et al. (2016) extend the TPB to show that environmental concern had a significant indirect effect on the adoption intention via the behavioral attitude. Best (2010) studied the relevance of environmental concern for the uptake of organic farming in Germany in a two-step approach. Specifically, they assessed the effect of farmers' environmental concern on the attitude towards organic farming for reducing negative environmental consequences and the impact of the latter on the subsequent implementation likelihood. The authors concluded that a favorable environmental attitude of farmers was associated with a more positive evaluation of organic farming which again lead to a higher adoption likelihood thereof. The fifth hypothesis is formulated accordingly:

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

Moral norms refer to an individual's perception of the (in)correctness of a specific behavior. The concept relates to perceived responsibilities or obligations to conduct or abstain from a certain behavior (Schwartz, 1977). Such norms are based on the evaluation of potential consequences of one's own actions (Arvola et al., 2008) and affect a range of individual actions (Dessart et al., 2019). Since the merits of sustainable farming practices have a public good character, moral norms may capture what a farmer perceives as a desirable contribution to society. Previous empirical studies support the role of moral norms as a predictor of intention in the context of farmer behaviors including environmentally related ones (Sok et al., 2021). More specifically, Rezaei et al. (2019) identified personal norms to directly determine Iranian farmers' intention to implement integrated pest management while Karimi and Saghaleini (2021) found moral norms to indirectly determine the intention to conserve range lands via the attitude towards this behavior. Furthermore, Bagheri et al. (2019) showed that favorable moral norms significantly reduced Iranian farmers' intention to use pesticides, directly and indirectly. The question persists whether the effect of moral norms on behavioral intention is of direct nature or whether it is mediated through attitude. Klöckner (2013) concluded from a meta-analysis based on 56 independent data sets that attitude partially mediates the impact of moral norms on behavioral intentions, emphasizing the relevance of both direct and indirect effect. This motivates the assessment of both of these effects on farmers' intention to adopt spot spraying in the present study and the corresponding hypotheses are formulated:

H6a. Perceived moral norms in favor of using spot spraying have a positive effect on the intention to use spot spraying for weed management.

H6b. Perceived moral norms in favor of using spot spraying have a positive effect on the attitude towards using spot spraying for weed management.

Figure 5.1 presents the structural model and the related hypotheses regarding farmers' intention to use spot spraying.

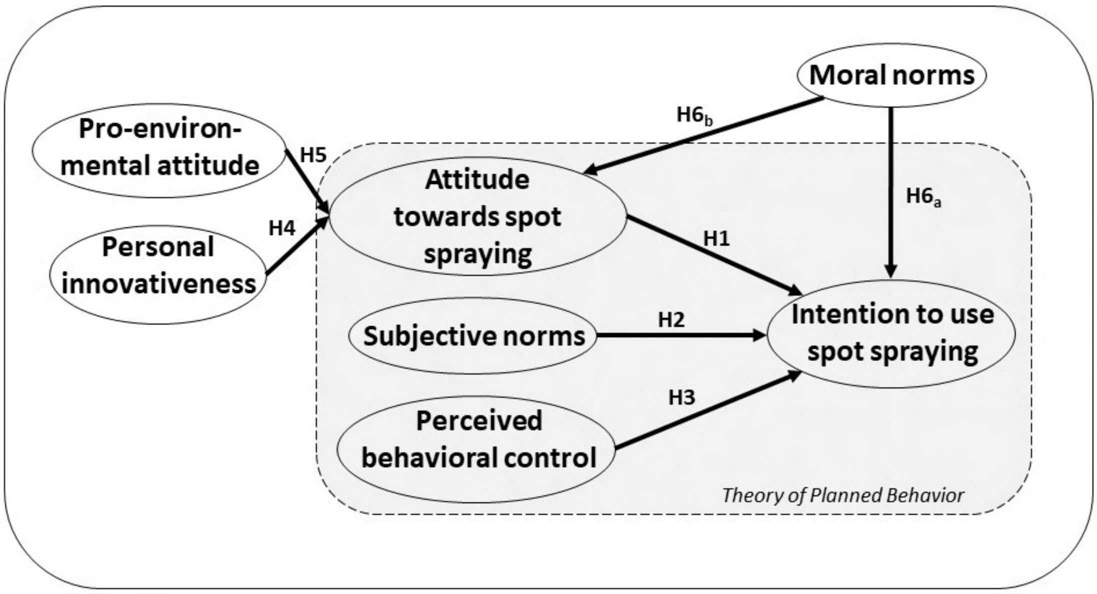

Figure 5.1: Structural model of farmers' intention to use spot spraying.

5.3 Methods

5.3.1 Questionnaire and behavioral constructs

Data collection took place between February and April 2022 with conventional arable crop farmers as target group. The online survey was distributed via email in several German federal states using multiple channels.[19] The survey started with two questions regarding participants' prior knowledge and use of SFT in general and spot spraying in particular. Subsequently, all participants received an informational text about the technology to create a common knowledge base regarding spot spraying. To analyze farmers' intention to adopt spot spraying according to the extended TPB model, the subsequent section contained a set of item questions representing the seven latent, multidimensional constructs attitude towards spot spraying (AttSS), subjective norms (SN), perceived behavioral control (PBC), intention (INT), pro-environmental attitude (AttEnv), personal innovativeness (PI) and moral norms (MN). For the formulation of indicator questions, validated scales from previous literature were used (see Supplementary Information) to guarantee robust construct measurement. Moreover, in adapting the indicators to the study context in line with the hypotheses, it was adhered to the principles of construct and scale compatibility whenever possible (Sok et al., 2021). The focal behavior was framed regarding the specific action, time period, and context. Specifically, it was framed as farmers' intention to use spot spraying for herbicide-reduced weed management on parts of their own farmland within the next five years. The indicators of all constructs were operationalized via 7-point Likert scales (Fishbein and Ajzen, 2010). The survey concluded by requesting sociodemographic and farm related information. The questionnaire was pretested with 18 members of the Chamber of Agriculture of North Rhine-Westphalia, mostly active farmers, upon which the questions were slightly adapted.

[19]This present study is part of a larger investigation regarding SFT. Full presentation thereof would exceed the extent of this paper. Survey distribution channels and the questionnaire can be found in the Supplementary Information.

5.3.2 Analysis

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM),[20] a non-parametric variance-based estimation strategy that maximizes the explained variance in endogenous variables (Hair et al., 2017a). PLS-SEM was preferred over the covariance-based SEM due to the explorative nature of research and the complexity of the derived structural model including multiple constructs and respective items (Hair et al., 2019). PLS-SEM is also preferred since the path model includes formatively measured constructs (Hair et al., 2021). Additionally, PLS-SEM makes no assumptions regarding the distribution of the data (e.g., normality) and thus provides high flexibility (Hair et al., 2017a). This allows to extend existing theoretical frameworks and to derive model-based predictions (Hair et al., 2017b) rendering this method particularly useful to formulate recommendations for practitioners (Hair et al., 2021). PLS-SEM has been used to study extensions of TPB-based models (e.g., Karimi and Saghaleini, 2021; Michels et al., 2020a) and has been successfully applied to investigate technology adoption behavior in the agricultural sector (Bonke and Musshoff, 2020; Hüttel et al., 2022; Mohr and Kühl, 2021).

The theoretical constructs in PLS-SEM models are latent (unobservable) by nature requiring indirect measurement via sets of observable indicators which hold as proxies for the underlying constructs (Hair et al., 2017a). Accordingly, the analysis of PLS-SEM proceeds in two steps: First, the outer (measurement) model assesses the reliability and validity of the latent variables. Second, the inner (structural) model tests the strength of the associations among the latent variables. The evaluation criteria of the measurement model differ for reflectively and formatively measured constructs. In reflectively measured constructs, the direction of relationship goes from the construct to the indicators which reflect the same underlying theoretical domain and are thus assumed to be highly correlated. Items are interchangeable such that leaving one out does not substantially change the construct (Hair et al., 2017a). In formative latent variables, items are said to form the construct, i.e., the relationship goes from the indicator to the construct. Each item covers different aspects of the same conceptual domain, they are not interchangeable and leaving out one item can substantially change the meaning of the construct (Hair et al., 2017a).

[20] The analysis was performed in Smart PLS 4.0.9.5 (Ringle et al., 2022)

In order to find a medium-sized effect (Cohen's f^2 of 0.3), a power analysis assuming a power level of 80%, a significance level of 5%, and a set of 7 latent with a total of 23 observed indicator variables yielded a minimum sample size of 170 observations (Soper, 2023).

5.4 Results

5.4.1 Sample

The survey was started by 713 participants. Of those, 332 did not finish the questionnaire (dropout rate=45,4%) or refused to consent to the use of their anonymized survey responses (n=3). Furthermore, since neither chemical usage and therefore nor spot spraying is applicable for organic farmers, this farm type was excluded from the sample (n=45). The final data set consisted of 333 complete observations (Table 5.1) which exceeded the minimum required sample size. Regarding age, business type of farming (full-time/part-time), level of education, and farm size, the sample is not representative compared to statistics of the German farm population.[21]

The average age of respondents is 43.3 years; thus, approximately ten years below the German farmer population. With 80.0%, the share of full-time farmers in the sample is about twice as large compared to the underlying population. Furthermore, 48.0% of the participants cultivate 101 ha or more which exceeds the German average of 63.2 ha per farm. This is emphasized by the fact that around 90.0% of the sample was collected in the federal states of North Rhine-Westphalia, Bavaria, Baden-Wuerttemberg and Lower Saxony where average farm sizes are 43.8, 36.0, 36.6, and 72.7 ha, respectively. However, with 92.0% family-owned farms the sample is well representative of the German average (86,7%). In addition, with about 40.0% of participants carrying at least a bachelor degree, higher educated respondents are overrepresented. Lastly, 31.0% (35.0%) of participants have prior knowledge of SFT (spot spraying in particular). Given the outlined characteristics, the sample renders itself especially interesting to study the adoption intention of presumably innovative and venturous farmers (Tamirat et al., 2017).

[21] See the Supplementary Information for references used to compare the sample with the underlying farmer population.

Table 5.1: Sociodemographic and farm characteristics.

Variable	Mean/share (SD)	German farmer population[a]
Age in years	43.3 (11.7)	53.0
Education	58.0% vocational training, state-approved/master's certificate 37.0% Bachelor/Master degree, 1.5% doctoral degree 3.0% other	58.0% vocational training, state-approved/master's certificate 9.0% Bachelor/Master/ doctoral degree 33.0% other
Full-time farming	80.0%	41.8%
Family farm	92.0%	86.7%
Farm size (hectares)[b]		
0-5	0.6%	-
6-10	1.5%	-
11-20	5.1%	-
21-50	16.0%	-
51-100	29.0%	-
101-200	25.0%	-
>200	23.0%	-
Experience with smart farming technologies (1=yes, 0=no)	31.0%	N/A
Knowledge of spot spraying technology (1=yes, 0=no)	35.0%	N/A

n = 333
[a] See the Supplementary Information for references used for comparison.
[b] Due to substantial difference in farming structures across different German federal states it did not appear feasible to calculate and present shares of different farm size classes of the German farmer population averaged across all federal states. Average farm sizes per federal state can be found in the additional references in the Supplementary Information.

5.4.2 Descriptive statistics of observed indicators

Tables 5.2 and 5.4 provide descriptive statistics for the items of reflectively and formatively measured constructs, respectively, which entered the PLS-SEM. Mean values for all items of the construct adoption intention (INT) range from 3.13 to 3.36. Thus, farmers in this sample have, on average, a rather low intention to use spot spraying for weed management on parts of their fields within the next five years. The AttSS item values are somewhat higher ranging from 4.24 to 4.41. Accordingly, respondents perceive this technology as neutral to slightly positive. The item values of AttEnv range from 5.74 to 6.01 indicating a high average pro-environmental attitude in the sample. Noteworthy is that two standard deviations of the three AttEnv items are relatively low pointing to a high level of consistency in respondents' opinion with respect to the items. Moreover, farmers perceive little social pressure to adopt spot spraying (mean values for SN of 3.12 and 3.15). At the same time, they do feel a moral obligation to protect the environment by reducing herbicide application (mean values for MN ranging from 4.47 to 5.37). Respondents perceive themselves in general as innovative (mean values for PI ranging from 4.95 to 5.89). Finally, on average farmers neither agree nor disagree that they have the necessary resources to adopt spot spraying on their farms (mean PBC values between 4.16 and 3.50).

Table 5.2: Reflective constructs: descriptive statistics, indicator reliability, internal consistency reliability and convergent validity.

Construct	Statement	Mean (SD)	Loading[c]
Intention to adopt spot spraying[a] (CR=0.942, AVE=0.895)			
INT_1	I will try to use spot spraying as a weeding method on parts of the acreage currently under cereal or root crops cultivation within the next five years.	3.34 (1.90)	0.941***
INT_2	I intend to use spot spraying as a weeding method on parts of the acreage currently under cereal or root crops cultivation within the next five years.	3.13 (1.88)	0.961***
INT_3	I want to use spot spraying as a weeding method on parts of the acreage currently under cereal or root crops cultivation within the next five years.	3.36 (1.98)	0.935***
Attitude towards spot spraying[a] (CR=0.942, AVE=0.885)			
AttSS_1	I think that the use of a spot spraying technology for weed management can increase profitability of my farm.	4.24 (1.80)	0.902***
AttSS_2	I think that the use of spot spraying technology for weed control can be advantageous for my farm.	4.40 (1.78)	0.958***
AttSS_3	All in all, I think that the use of spot spraying technology for weed control can prove to be useful for my farm.	4.41 (1.80)	0.961***
Pro-environmental attitude[b] (CR=0.903, AVE=0.809)			
AttEnv_2	Respecting the earth: harmony with other species.	6.00 (1.13)	0.914***
AttEnv_3	Unity with nature: fitting into nature.	5.74 (1.32)	0.890***
AttEnv_4	Protecting the environment: preserving nature.	6.01 (1.97)	0.894***

continued . . .

... continued

Construct	Statement	Mean (SD)	Loading[c]
Subjective norms[a] (CR=0.928, AVE=0.933)			
SN_1	People who are important to me regarding my business decisions on farm think that I should use spot spraying technology.	3.12 (1.75)	0.966***
SN_2	People who influence my business decisions on farm think that I should use spot spraying technology.	3.15 (1.79)	0.966***
Moral norms[a] (CR=0.882, AVE=0.809)			
MN_1	I would feel guilty if I did not try to reduce the applied amounts of herbicides on my fields in order to protect the environment and strengthen biodiversity.	4.47 (1.99)	0.872***
MN_2	When I reduce the amounts of applied herbicides on my fields to protect the environment and strengthen biodiversity I feel like a better farmer.	5.37 (1.68)	0.914***
MN_3	I feel morally obliged to reduce the amounts of applied herbicides on my fields in order to save the environment and strengthen biodiversity.	4.98 (1.88)	0.913***
Personal innovativeness[a] (CR=0.853, AVE=0.692)			
PI_1	I am generally very curious about how new technologies work.	5.89 (1.11)	0.830***
PI_2	I often research information on new technologies (magazines, internet, technology experts etc.).	5.29 (1.48)	0.835***
PI_3	I like to try out/experiment with new technology.	4.95 (1.56)	0.854***
PI_4	I like to be around colleagues who experiment with new technologies.	5.11 (1.51)	0.807***

Threshold values: loadings>0.708, CR>0.7, AVE>05.
n = 333
[a] 7-point Likert scale items ("Please indicate your level of agreement" – 1 "I strongly disagree"; 7 "I strongly agree").
[b] 7-point Likert scale items ("Please indicate how important the below values are for you as guiding principles in your life?" – 1 "not important at all"; 7 "extremely important").
[c] Significance code: ***p<0.001, **p<0.01, *p<0.05.

5.4.3 Measurement model evaluation

Reflectively measured constructs were evaluated for indicator reliability, internal consistency reliability, convergent validity and discriminant validity (Hair et al., 2017a).[22] Indicator reliability describes how much of each indicator's variance is captured by

[22]The here presented measurement model evaluation results (Tables 2–4) refer to the extended model (H1–H6_b) after deletion of several items which did not meet the evaluation criteria. Respective results for the baseline TPB do not differ substantially and are, thus, not explicitly discussed. Supplementary analysis results for the measurement and structural models of the baseline and extended model are available in the Supplementary Information.

its construct. Significant standardized loadings above 0.708 are considered acceptable since their squared value of 0.5 or larger implies that the construct explains at least 50 percent of the indicator's variance. Internal consistency reliability, the degree to which indicators measuring the same construct are correlated with each other, was tested via composite reliability (CR) at a threshold level of 0.7. Composite reliability estimates of 0.95 or higher suggest redundancy among items which reduces construct validity and potentially causes undue correlation of the items' error terms (Hair et al., 2021). Convergent validity, i.e., the magnitude of the average variance of all indicators (the mean value of squared indicator loadings) captured by a respective construct, was assessed via the average variance extracted (AVE) with a minimum acceptable value of 0.5. Finally, to assess whether the constructs are empirically distinct from one another (discriminant validity) the heterotrait-monotrait ratio was assessed (Henseler et al., 2015) with a threshold value that should be below 0.85. The assessment of the data based on the discussed criteria revealed factor loadings between 0.807 and 0.962 indicating high indicator reliability for all reflective constructs. CR values are all above 0.7, however, with very high composite reliability values ($\geq$0.95) for the constructs AttEnv and SN. After deleting one item of each of these constructs, respectively, all CR values lie in the desired range. The AVEs are above the threshold value of 0.5 for all constructs indicating adequate convergent validity. Finally, the HTMT ratios are below the 0.85 threshold yielding discriminant validity between constructs (Tables 5.2 and 5.3).

Table 5.3: Reflective constructs: discriminant validity.

	AttEnv	**AttSS**	**INT**	**MN**	**PI**
AttSS	0.213	-	-	-	-
INT	0.279	0.693	-	-	-
MN	0.548	0.459	0.468	-	-
PI	0.381	0.306	0.410	0.315	-
SN	0.193	0.671	0.703	0.422	0.278

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

The evaluation of formatively measured constructs required different steps (Hair et al., 2021). Specifically, indicator collinearity and the significance and relevance of indicator weights and loadings were evaluated (Hair et al., 2017a). High correlation between indicators of formative constructs increases the standard errors of indicator weights which may cause imprecise or incorrect estimation (Hair et al., 2017a). The variance inflation factor (VIF) allows for assessing indicator collinearity with values above 5 being indicative of high collinearity. Lastly, indicator weights, loadings and their significance were inspected for relative and absolute statistical item importance. For the only formatively measured construct PBC, VIFs of all items lie below the threshold, i.e., no case of indicator collinearity is identified. The weights of two items, however, are insignificant. In line with Hair et al. (2017a), a subsequent inspection of respective loadings and their significance reveals sufficient magnitude and significance for PBC_1. By contrast, an insignificant outer loading of below 0.5 for PBC_2 yielded no absolute statistical relevance of this indicator for the construct and it was thus dropped from the data. Considering the different magnitudes of the retained items, the construct is mainly formed by PBC_3 with PBC_1 being of marginal relevance (Table 5.4).

Table 5.4: Formative constructs: descriptive statistics, indicator collinearity, weights and loadings.

Construct	Statement	Mean (SD)	VIF	Weight[b]	Loading[b]
Perceived behavioral control[a]					
PBC_1	I have sufficient knowledge and skills to implement spot spraying technology on my farm.	4.16 (2.05)	1.463	0.072	0.611***
PBC_3	I have sufficient technical resources and time to implement spot spraying technology on my farm.	3.50 (1.84)	1.463	0.958***	0.998***

Threshold values: VIF<5.
n = 333
[a] 7-point Likert scale items ("Please indicate your level of agreement" – 1 "I strongly disagree"; 7 "I strongly agree").
[b] Significance code: ***p<0.001, **p<0.01, *p<0.05.

5.4.4 Structural model evaluation and testing of hypotheses

For the structural model evaluation, multicollinearity among endogenous variables was assessed via the VIFs (threshold=5; Hair et al., 2017a) to rule out redundancy. With all VIFs ranging between 1.148 and 1.768, no issues of multicollinearity are present. Adjusted R^2 and Stone-Geisser criterion Q^2 for the endogenous variables INT and AttSS provide information on the model variance explained (in-sample predictive power) and out-of-sample predictive relevance, respectively (Hair et al., 2017a). The latter was calculated in an iterative blindfolding procedure with an omission distance of ten. Furthermore, because PLS-SEM does not assume normality of data, a bootstrapping procedure with 10,000 iterations was applied to calculate 95% confidence intervals of the standardized path coefficients (Hair et al., 2017a). Standardized coefficients below 0.2, between 0.2 and 0.5, and above 0.5 represent a small, medium and large effect, respectively (Fey et al., 2023). The approximate overall model fit was examined via the standardized root mean square residual (SRMR) (Henseler et al., 2016). Finally, although the latent constructs are conceptually distinct, they are often found to be correlated (Ajzen, 2020) as displayed in Table 5.5 for our case. However, as the HTMT ratios are all below the 0.85 threshold, discriminant validity between constructs is secured.

Table 5.5: Correlation of latent variables of extended TPB model.

	AttEnv	**AttSS**	**INT**	**MN**	**PBC**	**PI**	**SN**
AttEnv	1	-	-	-	-	-	-
AttSS	0.200***	1	-	-	-	-	-
INT	0.254***	0.652***	1	-	-	-	-
MN	0.488***	0.419***	0.426***	1	-	-	-
PBC	0.169***	0.318***	0.449***	0.247***	1	-	-
PI	0.335***	0.275***	0.368***	0.275***	0.339***	1	-
SN	0.176***	0.625***	0.657***	0.382***	0.362***	0.250***	1

***p<0.001
AttEnv Pro-environmental attitude, *AttSS* Attitude towards sport spraying, *INT* Intention, *MN* Moral norms, *PBC* Perceived behavioral control, *PI* personal innovativeness, *SN* subjective norms.
n = 333.

Figure 5.2 (Supplementary Information, Table 6) presents the path analysis results of the baseline TPB model.[23] For the focal construct INT, moderate in-sample predictive power (R^2_{adj}=0.547) and good out-of-sample predictive model accuracy (Q^2=0.539) are found. The SRMR has a value of 0.029 indicating good approximate model fit. The estimation yielded empirical evidence for the first three hypotheses. Specifically, medium effect sizes for AttSS (H1), SN (H2), and PBC (H3) where found suggesting a positive association of each construct with intended spot spraying adoption. However,

[23]In following recommendations by Amrhein et al. (2019) and Heckelei et al. (2023), only the magnitude and 95% confidence intervals are presented and discussed here while further information, e.g., p-values, are presented in the Supplementary Information, Tables 6 and 7.

the 95% confidence intervals of AttSS and SN indicate that compatible effects in the population could range from a medium to an almost large effect while the confidence interval for PBC indicate that the effect size could range from small to medium.

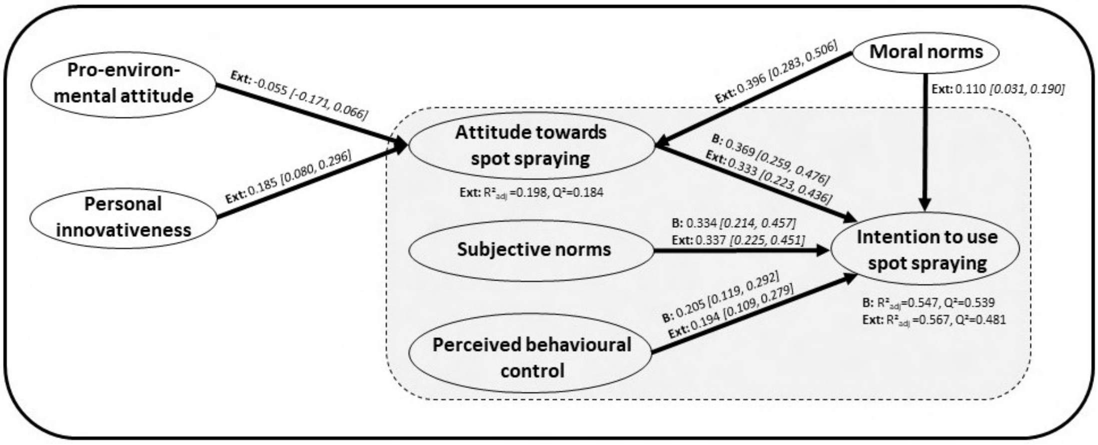

Figure 5.2: Estimated Theory of Planned Behavior path coefficients, R^2 and Q^2 values of the baseline model (B) and the extended model (Ext), respectively.

Note: The dotted line encompasses all behavioral constructs of the theoretical model in its original form. Values in parentheses indicate the lower and upper bound, respectively, of the 95% confidence intervals based on a bootstrapping procedure with 10,000 resamples.

The path analysis for the extended model is displayed in Figure 5.2 (Supplementary Information, Table 7). The R^2_{adj} values for INT and AttSS amount to 0.567 and 0.198 indicating moderate and weak explanatory power, respectively. The slightly higher R^2_{adj} value for INT in the extended model suggests marginal model improvements compared to the baseline model. Positive Q^2 values for INT and AttSS of 0.481 and 0.184, respectively, indicate that the extended model has good out-of-sample predictive relevance. Furthermore, a SRMR value of 0.096 suggest good approximate model fit. Based on the model specification, empirical evidence in line with all pre-registered hypotheses but for H5 was found in this sample (Figure 5.2). First, the results of the baseline model are by and large reproduced by the extended model. The estimation yielded medium effect sizes for AttSS (H1) and SN (H2) whereas a small effect was estimated for PBC (H3). Second, the assessment of the model extensions yielded mixed results. A small direct effect of PI on AttSS implies that PI is a small, yet relevant antecedent of AttSS in the presented sample according to the model specification (H4). This effect translates into a small total effect from PI on INT. For the path from MN on

AttSS, a medium-sized effect was estimated ($H6_b$). However, the confidence interval shows that compatible effect sizes could range from medium to large. The small indirect effect size for MN on INT via AttSS, together with the small direct effect of MN on INT ($H6_a$) suggests a relevant total effect of MN on INT in this particular sample. Lastly, a small negative relation between AttEnv and AttSS was estimated (H5). Yet, the confidence interval includes both negative and positive values. Thus, the results do not substantiate H5, i.e., the effect of AttEnv on AttSS is ambiguous and statistically not significant. This translates into a similar pattern for the total effect of AttEnv on INT.

5.5 Discussion

5.5.1 General findings

With sufficient in-sample and out-of-sample predictive power in the baseline and the extended model, the study shows that farmers' adoption intention is well explained by the TPB. This confirms the adequacy of this behavioral theory to assess adoption intention of agricultural innovations (cf. Sok et al., 2021). Furthermore, the extension of the TPB by three constructs derived from empirical research provides additional valuable insights for the understanding of farmers' adoption behavior as well as for future studies. The study arrives at medium-sized effects of the attitude towards spot spraying on intended spot spraying adoption in the baseline and extended model. These results are in line with findings of Rezaei et al. (2019) on integrated pest management, of Beza et al. (2018) on SMS service for agricultural data collection and of Michels et al. (2020a) on intended smart phone app use for crop protection purposes. The latter even find a large effect of attitude on intention. Surprisingly, however, in studies looking at technologies more comparable to spot spraying, e.g., digital nitrogen fertilization technology (Hüttel et al., 2022) and agricultural AI systems (Mohr and Kühl, 2021) no effect could be identified. The authors of the latter two studies argue that the assessed technologies were too complex and yet too unfamiliar for farmers to have already formed an attitude strong enough to influence intention. Arguably, spot spraying has comparable degrees of complexity and novelty. However, despite low diffusion of the technology, farmers in this sample seem to have developed an attitude which is, on average, in favor of intended adoption.

The effect of subjective norms in the baseline and the extended model of this study was confirmed as a relevant predictor of adoption intention with a medium effect size. While Mohr and Kühl (2021) found no effect of social norms on the acceptance of the general concept of AI systems in agriculture studies focusing on intended adoption of (more) specific innovations, e.g., smartphone app use (Michels et al., 2020a) and variable rate fertilization (Hüttel et al., 2022) do, although the respective effect size is small to medium. Similar to the latter two technologies, spot spraying is already commercially available which suggests that information and first experiences are already shared within farming communities. Nonetheless, due to novelty and technological complexity implying high requirements with respect to on-farm infrastructure and personal competences farmers often perceive the implementation and use of digital farming technologies challenging (Mohr and Kühl, 2021). The opinions and experiences of innovation leaders may be crucial for the majority of farmers to overcome personal restraints, gather technical know-how, and gain the confidence to introduce spot spraying on their own farm. Beyond the here discussed pre-registered impact of subjective norms on intention, it is plausible that the professional environment may co-determine farmers perceived moral obligations. Therefore, we conducted further exploratory tests which can be found in the Supplementary Information.

The relevance of perceived behavioral control, the third determinant of intention in the TPB, was confirmed in both estimated models with a small to medium effect size. While comparable results were identified in studies focusing on the adoption intention of sustainable innovations (e.g. Bonke and Musshoff, 2020; Dong et al., 2022; Rezaei et al., 2019), the picture is less clear for research investigating digital farming technologies, specifically. Whereas Mohr and Kühl (2021) find a large effect of PBC on AI agricultural system acceptance, Hüttel et al. (2022) find no support for PBC as a determinant of the intention to adopt digital fertilization methods. Noteworthy, the findings of the present study show that, although of relevance, perceived behavioral control has a smaller impact on spot spraying adoption intention than the attitude towards the technology and subjective norms to use it. This partly corresponds to previous studies on, e.g., intended adoption of drip irrigation (Wang et al., 2023), mixed cropping (Bonke and Musshoff, 2020), or integrated pest management (Rezaei et al., 2019). Although these mentioned innovations may not be comparable regarding their objectives and factor demands, their commonality is that they, similar to spot spraying, systematically change on-farm processes rather than affect single process steps. Thus, forming the intention to adopt such innovations may depend more strongly on personal attitudes and social influences, whereas aspects of perceived behavioral control, e.g., on-farm resources or operator skills may become more relevant for the actual implementation.

Moral norms, one of the literature-based model extensions, showed a medium total effect on intended spot spraying adoption in the extended model. This indicates that farmers who perceived moral obligations to reduce the amounts of applied herbicides on their field for environmental and societal benefits have a higher intention to adopt spot spraying. This is by and large in line with the findings of Karimi and Saghaleini (2021) and Bagheri et al. (2019) who show that moral norms increase farmers' intention to conserve rangelands and to reduce pesticide use in Iran, respectively. However, no other study assessing the role of this construct for the adoption intention of digital farming tools was identified, thereby limiting the integration of findings into the relevant context. The present study also indicates, that moral norms does not only have a small direct effect on the attitude towards spot spraying but it additionally influences the intention to adopt it indirectly via the attitude. Interestingly, the latter effect even slightly exceeds the former one in its overall magnitude on intention. While high perceived moral obligations to limit herbicide application were prevalent in the sample (Table 5.2) spot spraying may not necessarily have been the preferred option to achieve this ambition. Presumably, although no immediate implication of the data, the direct effect may become more important as spot spraying becomes more visible and accessible.

Two additional potential antecedents of the attitude towards spot spraying, namely pro-environmental attitude and personal innovativeness were considered in the extended model. The results show that, similar to moral norms, personal innovativeness influences the attitude of spot spraying, however, to a smaller extent. Thus, as expected the present study provides support for the hypothesis that farmers with an innovative mindset develop more favorable attitudes towards SFT and are subsequently more inclined to implement such technology on their farm (Mohr and Kühl, 2021). Conversely, the hypothesis that pro-environmental attitude positively impacts the attitude of spot spraying and indirectly influences also adoption intentions was not supported by the results of this study. This is in contrast to previous studies which show that a pro-environmental orientation positively impacts the uptake of pro-environmental behavior via more positive attitudes towards innovations (Best, 2010; Dessart et al., 2019). Again, we acknowledge that further intuitively plausible pathways of the impact of personal innovativeness and pro-environmental attitude were omitted in the extended model above. Please see the Supplementary Information for further exploratory analyses.

5.5.2 Policy implications

Based on the presented findings, a number of policy measures could be considered to unleash the "paradigm shift" towards a more sustainable food system associated with SFT (Lindblom et al., 2017). With subjective norms and the attitude of spot spraying as the most important drivers of adoption intention, the provision of local platforms to foster social interaction among farmers may be a starting point to promote the exchange of knowledge and experiences with respect to the uptake of digital innovations, thereby increasing the awareness of SFT within farming communities. Moreover, demonstrations and field days offered by regional agricultural ministries, chambers and technology experts may facilitate farmers' access to trustworthy information sources to address potential restraints and enhance their attitude regarding potential benefits of SFT (Toma et al., 2018). The behavioral attitude in our study is linked to the perceived, primarily economic, benefits of the technology for farmers. On average, the sampled farmers only had a weak positive conviction that spot spraying could increase profitability of their farm (AttSS_1=4.24, Table 5.2). Furthermore, the average values for all items measuring adoption intention were below 4 ("I neither agree, nor disagree") suggesting restraint in our survey participants' adoption intentions. One option to address this could be an agri-environmental scheme which provides payments for the adoption of more sustainable agricultural practices to incentivize pro-environmental behavior in farming (Massfeller et al., 2022; Wuepper and Huber, 2022).

This study also reveals the relevance of moral norms as an important driver for farmers' attitude towards spot spraying and their intention to adopt it. Perceived moral obligations and norms develop over time and cannot be imposed by government regulation. Nevertheless, governmental campaigns to promote awareness for the environmental benefits of SFT might increase farmers' motivation to recognize and exert their own influence to shape this development.

Another determinant influencing farmers' intention to adopt spot spraying on their farm was perceived behavioral control. This construct was predominantly formed by the item

PBC_3 referring to sufficient technical resources and time to implement spot spraying (Table 5.4). In fact, high investment cost, time-consuming maintenance and unsuitable infrastructure on farm are frequently mentioned causes of reluctance among farmers to adopt digital innovations (Kernecker et al., 2020; Mohr and Kühl, 2021; Reichardt and Jürgens, 2009). Hence, financial support for the acquisition of new technology and infrastructure, and for the training of staff to operate and maintain new machines may help to overcome the barriers identified, thereby enabling farmers especially at the early stages of SFT development to overcome entry barriers and thereby promote the diffusion of those technologies.

Finally, we find that farmers with a higher inclination to learn and discuss about innovations tend to have a higher attitude of spot spraying which translates to higher adoption intentions. Westerink et al. (2017) could show that including farmers into spatially coordinated policy schemes had a positive influence on their collaboration behavior. For the present case, a similar approach which specifically targets innovative farmers may accelerate the dissemination of and exposure to SFT related information. This may have a positive effect on the overall perception and intended adoption of SFT among farmers who are part of such participatory schemes.

The assessment of the extended model yielded a slightly higher adjusted R^2_{adj} value for intention, i.e., the added constructs marginally increased the in-sample prediction power of the focal path model. Especially, moral norms renders itself a potentially relevant construct in future research on sustainable agricultural innovations uptake. Moreover, a medium-sized total effect, approximately evenly composed of a significant direct and indirect effect, of moral norms on intended adoption confirm the conclusion by Klöckner (2013) that both effects are relevant for environmental behavior.

5.5.3 Implications for future research and limitations

The question remains why, compared to moral norms and personal innovativeness, no definite effect of pro-environmental attitude could be detected. First, the lack of evidence might be due to the fact that, compared to all other constructs, pro-environmental attitude in this study was measured in a very general way comparable to a personality trait. It was neither linked to the weeding method nor to the objective to reduce herbicide application. However, it is recommended for all TPB constructs, the classic and the newly added, to comply with the principle of construct compatibility, i.e., to be specified according to the target, action, time frame, and context of the assessed behavior (Ajzen, 2020). For pro-environmental attitude this criterion was not met at all, while personal innovativeness and moral norms had a somewhat clearer connection to the target behavior. Strict adherence to construct compatibility has been shown to increase explained variance of endogenous variables (Sok et al., 2021) and may thus help to substantiate the here hypothesized relationships in future studies. Second, due to the economic framing of the items of the attitude towards spot spraying, a more favorable attitude towards spot spraying was observed among those survey participants who showed stronger agreement to the statements that spot spraying could be advantages, more useful or profitable for their business. Thus, the coefficient of the attitude towards spot spraying on adoption intention needs to be interpreted accordingly (cf. Barnes et al., 2019; Pierpaoli et al., 2013). However, no item of the attitude towards spot spraying asked participants whether they thought that spot spraying could mitigate negative environmental impacts which may be another explanation for having found no relevant association between pro-environmental attitude and the attitude towards spot spraying. Nevertheless, the environmental mitigation potential through, e.g., reduced agrochemical application is another important value proposition of SFT in general and spot spraying in particular, and should be included as a separate construct in future studies on intended SFT adoption (cf. Bonke and Musshoff, 2020; Rezaei et al., 2019).

Somewhat similar considerations apply to the subjective norms construct used in this study. The utilized item questions did not specify the background or field of expertise of individuals who might have influenced a farmer's adoption intention. However, in order to design targeted policy strategies, disseminate information about the economic and environmental potential, and to increase farmers' exposure to SFT, learning about specific channels of social influences is necessary. In this endeavor, Hüttel et al. (2022) found out that current users and other farmers had a positive effect on German farmers' perceived subjective norms while farm advisors had a negative influence on this construct. Addressing such promising channels to exchange information and experiences may arguably be an efficient way to promote digital farming technology adoption (Barnes et al., 2019).

Three main limitations mark the paper. First, resulting from the non-random online mode of survey distribution via email, the selected distribution channels (see Supplementary

Information), and the topic of the survey which may have been of varying interest to the addressed population, no representative sample could be generated and self-selection bias may be a concern (Weigel et al., 2021). This data set is therefore considered a convenience sample and we do not claim generalizability of the findings. Being biased towards younger, well-educated full-time farmers, our sample may have exhibited above average levels of environmental and moral attitudes alongside an emphasized interest in and attitude towards smart innovations. Our model effects for several behavioral measures may thus represent overestimations relative to the underlying population. Nevertheless, the survey participants likely represent the more innovative, venturous segment of the farmer population rendering respondents as such an interesting group to investigate. Supporting this farmer segment among which SFT adoption is most likely to be observed first should be of interest from a policy perspective. Such "early adopters" may act as role models, demonstrate the functionality of SFT and eventually initiate further diffusion of SFT among more hesitant colleagues (cf. Rogers, 2003).

Second, given the novelty of SFT, there is a relatively low level of diffusion and awareness among practitioners, as revealed in Table 5.1. Consequently, the analysis was constrained to assessing farmers' intentions rather than observing actual adoption. As a result, it is important to acknowledge that our results may suffer from hypothetical bias and that additional unrecognized factors may determine actual adoption at a later stage (Govindharaj et al., 2021). Furthermore, a high measure of intention does not necessarily lead to high levels of actual behavior. In fact, Ajzen (2020) lists several experimental design aspects and potentially unrecognized factors which may inhibit the closure of the so-called intention-behavior gap. Nonetheless, several studies in related fields have demonstrated that behavioral intention serves as a strong predictor of actual adoption (e.g., Bonke and Musshoff, 2020; Hüttel et al., 2022; Michels et al., 2020a; Moerkerken et al., 2020). Thus, we argue that our findings offer valuable insights into the underlying determinants of adoption to policy makers and practitioners.

Third, unobserved sample heterogeneity introduced by farmers with prior experience with SFT may have biased our results. We therefore conducted a multi-group analysis based on the binary grouping variable "Experience with smart farming technologies" (Supplementary Information). Due to uneven group sizes and low statistical power, the results require careful interpretation. Yet, we find no statistically significant differences in model coefficients between groups suggesting that a potential bias introduced by farmers with prior experience with SFT is low.

5.6 Conclusion

SFT tailor agricultural practices to smaller sections of the field or even individual plants which bears both economic and environmental potential. Nevertheless, because their implementation may fundamentally alter managerial on-farm processes, farm operators have shown to be hesitant to adopt SFT which causes the anticipated potential to remain widely unexploited. A more in-depth understanding of the drivers and barriers for their uptake is deemed necessary, which also considers behavioral factors influencing voluntary agricultural technology adoption for sustainable intensification–factors which so far have gained little attention in the SFT adoption literature. Thus, looking through a behavioral lens the Theory of Planned Behavior was applied and extended to assess the adoption intention of spot spraying, a sustainable weeding technology, in a sample of German crop farmers. Beyond demonstrating the adequacy of the TPB for the present case, the results highlight that social influences and farmers personal attitudes towards the technology have the strongest influence on intended spot spraying adoption. This is followed by farmers perceived moral obligations to reduce the applied amounts of herbicides. Furthermore, based on the extension of the model, important antecedents of attitudes towards spot spraying could be identified allowing for a better understanding of SFT adoption behavior.

The findings of this study offer insights for policy to advance the uptake of SFT exemplified by spot spraying. Measures that increase farmers' awareness of the benefits as well as schemes that strengthen their confidence to use novel digital technologies (Aubert et al., 2012; Toma et al., 2018) and facilitate communication and collaboration among innovative farm operators seem promising strategies to accelerate dissemination. Furthermore, and if properly designed, subsidies can help to secure profitability of socially beneficial innovations and thus level the playing field for this weeding method in the early diffusion phase. Early adopters who are morally determined to reduce negative environmental impacts of harmful farming practices may be an inspiration for their peers regarding technology-based ways of sustainable farming, raise local awareness and accelerate the diffusion of SFT within their professional networks Blasch et al. (2022).

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Compliance with ethical standards

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

Pre-registration

Pre-registration details are available via this OSF link: https://osf.io/fjd8h?view_only=c3587603a29e401d8257db17ee831ef3

CRediT authorship contribution statement

Philipp Feisthauer: Writing–review & editing, Writing–original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Monika Hartmann**: Writing–review & editing, Supervision, Methodology, Investigation, Conceptualization. **Jan Börner**: Writing–review & editing, Supervision, Project administration, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data to this article is available via this OSF link https://osf.io/nv8kp/?view_only=d1f3a00bd1e940b48b8c80b15e7cc4f8 in the folder with the name of this paper.

Supplementary Information

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