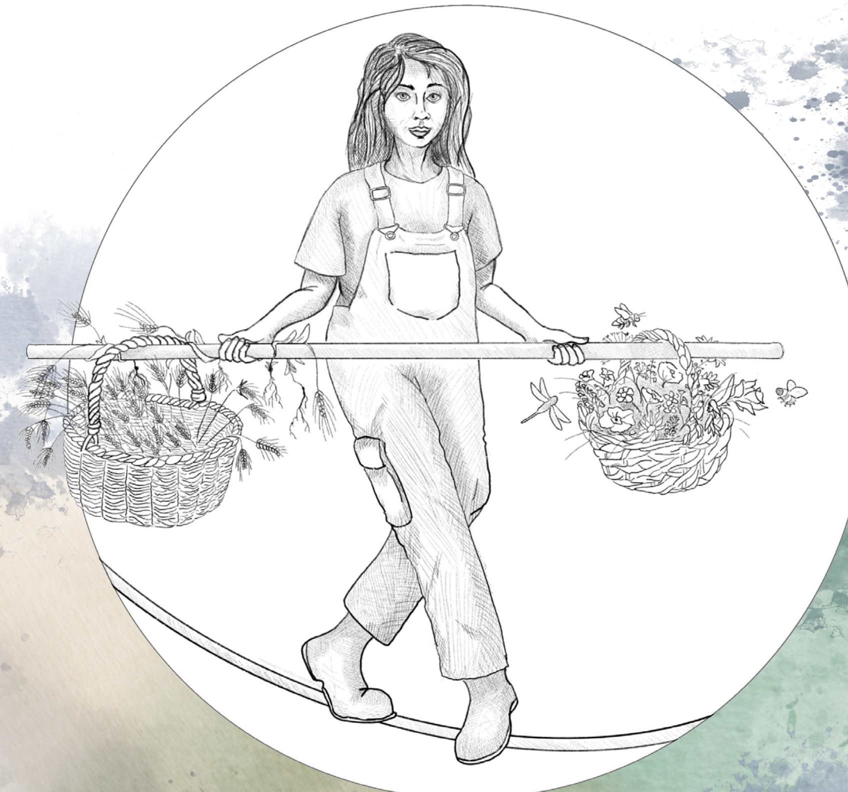
Annika Francesca Tensi

Sustainable Innovations on Arable Farms - Uptake and Effects



Sustainable Innovations on Arable Farms

Uptake and Effects

Annika Francesca Tensi

Propositions

1. Microbial applications cannot be compared with mineral fertilisers and pesticides in terms of sustainability.
   (this thesis)

2. A single innovation does not increase the sustainability of arable farms.
   (this thesis)

3. Animal testing is a necessary and justified means to scientific advancements.

4. Trees have intelligence.

5. Predatory journals burn public money.

6. Starting a PhD with a replication study benefits the candidate and scientific progress.

7. Only evidence-based, anticipatory and strictly enforced policies can stop environmental degradation.

Propositions belonging to the thesis, entitled

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Annika Francesca Tensi
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Sustainable Innovations on Arable Farms

Uptake and Effects

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Sustainable Innovations on Arable Farms

Uptake and Effects

Annika Francesca Tensi

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Gutta cavat lapidem, non vi, sed saepe cadendo.

Ovid

Contents

List of Figures

List of Tables

Acronyms

AIC	Akaike-Information Criterion
AIS	Agricultural Innovation Systems
BCW	Behaviour Change Wheel
BoD	Benefit-of-the-Doubt (index)
CAP	Common Agricultural Policy
CBS	*Centraal Bureau voor de Statistiek*, Central Agency for Statistics
CDF	Cumulative Density Function
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CO_2	Carbon dioxide
COM-B	Capability, Opportunity, Motivation, Behaviour
COVID-19	Coronavirus Disease 2019
CPT	Cumulative Prospect Theory
CRRA	Constant relative risk aversion
D&L	Drichoutis & Lusk, referring to their 2016 MPL lottery
DEA	Data Envelopment Analysis
DLG	*Deutsche Landwirtschafts-Gesellschaft*, German Agricultural Society
EFA	Exploratory Factor Analysis
EU	Expected Utility
EU	European Union
Eurostat	European Statistical Office
EUT	Expected Utility Theory
EC	European Commission
FADN	Farm Accountancy Data Network
FAIR	Findability, Accessibility, Interoperability, and Reuse (of digital assets)

FAO	Food and Agricultural Organization of the United Nations
FSDN	Farm Sustainability Data Network
fert	fertiliser(s)
GHG	Greenhouse Gas (emissions)
GPS	Global Positioning System
H&L	Holt & Laury, referring to their 2002 MPL lottery
IPCC	Intergovernmental Panel on Climate Change
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
KWIN-AGV	*Kwantitatieve Informatie Akkerbouw en Vollegrondsgroenteteelt*, Quantitative information on arable farming and field vegetables
ma	microbial applications
MC	Monte Carlo (simulation)
MLE	Maximum Likelihood Estimation
MPL	Multiple Price Lists
NPK	Nitrogen, Phosphorus, Potassium
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Square
OSF	Open Science Framework
PERT	Project Evaluation and Review Technique
PFC	Production Function Category
PPP	Plant Protection Products
R&D	Research and Development
RCT	Randomised Control Trial
RDU	Rank Dependent Utility (theory)
RIVM	*Rijksinstituut voor Volksgezondheid en Milieu*, Dutch National Institute for Public Health and the Environment
RMSEA	Root Means Square Error of Approximation
SARS-CoV-2	Coronavirus, see also "COVID-19"
SD	Standard Deviation
SDG	Sustainable Development Goal
SI	System of Innovation (approach)
SIMBA	Sustainable Innovation of Microbiome Applications in Food System
SME	small- and medium-sized enterprises

SUD	Sustainable Use of Pesticide Directive
TPB	Theory of Planned Behaviour
TLI	Tucker-Lewis Index
UAA	Utilised Agricultural Area
UN	United Nations
WEcR	Wageningen Economic Research

Chapter 1

General Introduction

Agri-food production is confronted with an increase in world food demand by more than 50% until 2050, compared to 2010, caused by global population growth and changes in dietary needs (World Resources Report: Searchinger et al. (2018)). Currently, the world's overall demand for food is satisfied with the aid of optimised agronomic practices, fertilisers and plant protection products (PPP), and genetically improved crops (Spiertz 2010). Agricultural productivity gains through technological innovations can help to ensure food security and relieve environmental pressures (Fuglie 2018).

However, over the last 60 years, intensified arable farm production came at a cost for ecosystems and biodiversity (Pimentel 1996). For instance, nitrogen fertiliser overuse damages aquatic and terrestrial ecosystems through eutrophication (Bodirsky et al. 2014), and causes water pollution and loss of biodiversity (Erisman 2021). Intensive agricultural practices and their degradation of agricultural soils (Tilman 1999) can have serious consequences for food security (Kopittke et al. 2019). The degradation of soils has led to a 23% reduction in productivity of the global terrestrial area (IPBES 2019b). Further, the numbers of farmland birds (Stanton et al. 2018; Butler et al. 2009) and insect biomass in fields and meadows (Hallmann et al. 2017; Forister et al. 2011) are declining. While agri-food production values tripled between 1970 and 2016, pollinator diversity and soil organic carbon declined, indicating that these production increases cannot be sustained indefinitely (IPBES 2019b). Apart from affecting ecosystems and natural habitats, agri-food production also accelerates climate change (Clark et al. 2022). According to the 2022 report of the Intergovernmental Panel on Climate Change (IPCC), 22% of total net anthropogenic greenhouse gas (GHG) emissions could be attributed to agriculture, forestry and other land uses in 2019 (Pörtner et al. 2022).

At the same time, agri-food production is negatively affected by environmental degradation and climate change. With the loss of pollinator services comes the risk of losing global crop output worth between USD 235 and USD 577 billion (IPBES 2019b). Increasing temperatures have already decreased crop yields and grassland quality, and increased yield variability (Pörtner et al. 2022).

Climate change increases the number and severity of extreme weather events such as droughts and floods which diminish yields. For instance, lower yields have been observed in European (Trnka et al. 2014) and global (Asseng et al. 2014) wheat production. With climate change, new pests and diseases emerge and old ones become increasingly powerful, for example in Dutch potato production (Goffart et al. 2022). All in all, global warming impairs food security. Global warming also has economic effects. The majority of evidence suggests that global warming leads to economic losses (Ortiz-Bobea et al. 2021) which disproportionately affect low-income countries (Mendelsohn and Williams 2006; Tol 2009), but proponents of a so-called 'technological fix' state that innovations for climate adaptation could also offer favourable economic returns (Baldos et al. 2020).

Against the backdrop of environmental degradation and climate change, global supply chains were most recently disrupted through the global COVID-19 pandemic[1] hitting Europe in the beginning of 2020 and the war of Russia against Ukraine starting in February 2022. Both the pandemic and the war showed how globalised supply chains with their interdependencies are susceptible to failure (OECD and FAO 2022). The COVID-19 pandemic lead to market disruptions, which affected farmers globally. We observed demand side shocks driven by consumer stockpiling behaviour and sudden changes in consumption patterns (Coopmans et al. 2021). Farmers had to deal with labour shortages, difficulties in material supply and price changes that lowered farm income (Hobbs 2020; Stephens et al. 2020). Then, the Russian invasion of Ukraine – the country that is also called the breadbasket of Europe, signalling the importance of the country in food production – disrupted global supply chains by reducing Ukraine's agri-food export capacity (OECD 2022). Lower global food supplies and food price increases tightened existing challenges induced by population growth and climate change, and fuelled by the COVID-19 pandemic (Caprile and Pichon 2022). Energy and fertiliser price increases and agri-food shortages led, especially in low-income countries, to food insecurity (Van Meijl et al. 2022).

Taking population pressure, environmental challenges and market disruptions together, the importance of sustainable transformation of the agri-food system becomes more pronounced. The agri-food system comprises the entire network and interlinked value-adding activities of actors "involved in the production, aggregation, processing, distribution, consumption and disposal of food products from agriculture [...] and food industries, along with the broader economic, societal and physical environments in which these activities are embedded" (Nguyen (2018), as cited in and adapted from von Braun et al. (2021, p. 748)). These actors include primary producers, suppliers,

[1] The coronavirus disease (or COVID-19) causes severe pneumonia and can be fatal for humans. The disease posed challenges for health care systems all over the world. Starting in China at the end of 2019, but being highly transmissible, the coronavirus spread over the world within just a couple of months (Hu et al. 2021). All European countries, including the Netherlands, brought public life to a halt in March 2020 to limit the spread of the virus.

processors and retailers, consumers, governmental institutions and policy makers, and actors from science, technology and innovation sectors. Agri-food system transformation is linked to the Sustainable Development Goals (SDGs) adopted by the United Nations (UN) in 2015. The SDGs are embedded in the Agenda 2030 and a "call to action to end poverty, protect the planet, and ensure [...] peace and prosperity" (UNDP 2023). The SDGs are linked as such that development must balance all three pillars of sustainability, i.e. the environmental, the social and the economic. Agri-food system transformation refers to fundamental changes to the agri-food system implemented with the aim, for instance, to reach climate neutrality and achieving the SDGs (von Braun et al. 2021). According to von Braun et al. (2021), "transformation is a never-ending process [..], transition is the movement from one state to another, and evolution is the process of change" [p. 749].

Historically, we have seen many transitions between agricultural production systems. The first agricultural revolution represents the transition from hunting and gathering to settled agriculture, the second falls together with the industrial revolution in the 18th century, and the third revolution, also called Green Revolution (Kush 2001), describes the mechanisation and productivity increases through artificial fertilisers and chemical PPP. All of these revolutions were radical at the time (Harari 2014). Yet, transitions of the past have always appeared incrementally over a long period of time. Considering population growth, climate change projections and ecosystem changes, the latest IPCC and Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) reports leave little doubt that the global agri-food system needs to rapidly adapt and develop mitigation mechanisms (Pörtner et al. 2022; IPBES 2019a). Innovations have played an important role in past agricultural transitions (Alston and Pardey 2021), which highlight their importance for the present agricultural transition (Herrero et al. 2020; Rose et al. 2021; Riccaboni et al. 2021; McKillop et al. 2018). Despite their importance in mitigating climate change and the benefits that they are providing, the diffusion of technologies designed to curtail environmental externalities is slow (Fuglie and Kascak 2001).

The European Commission's (EC) Farm to Fork strategy describes innovations as instrumental to 'resolve tensions, develop and test solutions, overcome barriers and uncover new market opportunities' (EC 2020). The Farm to Fork strategy is the European Union's (EU) answer to the aforementioned societal, environmental and climate challenges. One of the main objectives of the Farm to Fork strategy is to reduce chemical and hazardous PPP use by 50% and fertiliser use by at least 20% by 2030 (EC 2020). The Farm to Fork strategy defines agriculture's contribution to reach the objectives of the European Green Deal. The Green Deal is a package of legally binding policy initiatives that aims to reach climate neutrality by 2050, social justice and security, and to decouple growth from use of resources. These objectives were implemented in the latest reform of the EU's Common Agricultural Policy (CAP) (European Commission 2020a). The CAP is one of the first common European policies, established in 1962, just five years after the Treaty of Rome created the European Economic Community. In its early days, the CAP influenced price levels and protected the agri-food market with the goal to stabilise prices and thereby production (Renes 2009). The CAP has gone through numerous reforms, shifting from a focus on agricultural production to environmental protection (Blandford et al. 2014). The most recent CAP reform aims at i) food security through stable agricultural production, ii) sustainable use of natural resources and mitigating climate change, and iii) economic and social vitality in rural areas (European Parliament and Nègre 2023). As such, a shift away from the prevailing paradigm of conventional agricultural intensification towards various forms of sustainable agriculture can be observed (Skrimizea et al. 2020). The overall goal is to make food systems resilient to crises, environmentally friendly and fair, efficient and competitive (European Commission 2020b).

In light of the Farm to Fork strategy's objectives to reduce PPP and fertiliser use, sustainable innovations that reduce hazardous input use while maintaining food security and efficiency are important. One example of such a sustainable innovation are microbial applications. Microbial applications can decrease the need for PPP and fertilisers (Gong et al. 2020; Pertot et al. 2017). In microbial applications, beneficial microorganisms, such as bacteria, algae, fungi and viruses (Tshikantwa et al. 2018), with complementing traits are combined (Bhattacharyya et al. 2016; Compant et al. 2019). Microbial applications rely on the enhancement of ecosystem services by exploiting ecological processes (Therond et al. 2017). They can substitute or complement artificial fertilisers and chemical PPP in arable farming (Elnahal et al. 2022). In the EU, they are currently categorised as PPP or biocides (Sundh and Eilenberg 2021), even though they function as biocontrol agents, biostimulants and/or biofertilisers (Marrone 2019). As such, the definition of microbial applications is not clear-cut. In line with the prevalent use of the term, in this thesis, microbial applications are defined as a combination of biopesticides and biofertilisers. Microbial applications can be a granulate or in powder form. Both can be put directly in the soil together with the seeds, dissolved in water to use in irrigation, or suspended in liquid for seed coating.

Recent research shows promising results on the usage of microbial applications in agri-food production. For example, microbial applications have been found to increase the resilience, quality and productivity of crops, suppress plant diseases, and control pathogens, while reducing the need for the application of chemicals (e.g. Gouda et al. 2018; Gong et al. 2020; Pertot et al. 2017). Microbial applications promote plant growth by stimulating biological nitrogen fixation and nutrient uptake (Wezel et al. 2014), dissolving phosphate and relieving abiotic stresses (de Souza et al. 2015). Certain microorganisms stimulate a crop's defence mechanisms (Singh and Trivedi

2017). Further, microbial applications can be deployed as a remedy against the impacts of intensified climate change, such as degraded soils and droughts (Hutchins et al. 2019). Climate change will make biological nitrogen fixation and uptake even more important as the increase in atmospheric carbohydrate reduces nitrogen in the soil. Likewise, it affects photosynthesis and root activity, modifies plant pests and pathogens, and changes plant functioning. Microbial applications that combine the benefits of multiple microorganisms can relieve these stresses (Bhattacharyya et al. 2016). From a technical point of view, the success of microbial applications depends predominantly on their efficacy and versatility under field conditions (Parnell et al. 2016; Timmusk et al. 2017). Despite these promising recent research results on the effectiveness of microbial applications, current uptake of microbial application products by arable farmers remains low (Russo et al. 2012), which is – amongst others – the concern of this thesis.

In the remainder of the introduction, definitions and background on i) sustainability and agriculture, ii) sustainable agricultural innovations and iii) innovation uptake are provided. Then, the problem statement of this thesis is defined. Last, the overall objective and the four research questions along with introductions to the four research chapters are given.

1.1 Sustainability & Agriculture

The concept of sustainable development gained prominence through the Brundtland report in 1987. In the report, officially entitled *Our Common Future*, sustainable development has been defined as “development that meets the need of the present without compromising the ability of future generations to meet their own needs” (World Commission on Environment 1987). Nowadays, sustainable development is often conceptualised with the three pillar approach, also known as the ‘triple bottom line’ or ‘people, planet, profit’ idea (Barkemeyer et al. 2014). In this conceptualisation of sustainability, environmental, social and economic aspects of (business) activities need to be balanced (Elkington 1994). The three pillar approach provides a measurable and actionable framework to sustainable development, but the necessary trade-offs between the three pillars need to be transparent and consider limits to growth. The objective is to improve overall sustainability, which is constrained by given trade-offs between the three pillars. How to weight and balance the given trade-offs is a normative question. For instance, none of the three pillars should be improved by overly decreasing the performance of another pillar.

1

Sustainable agriculture is the solution to environmental problems faced and caused by agri-food production. In line with the conceptualisation of sustainability, sustainable agriculture meets the needs of existing and future generations, while also ensuring profitability, environmental health, and social and economic equity. Further, sustainable agriculture strengthens all four aspects of food security while being confined by the three pillars of sustainability. So, sustainable agriculture strengthens food availability, access, utilisation and stability, while being environmentally, economically and socially responsible over time (FAO 2014). Sustainable agriculture is not tied to one specific type of farming, like organic, regenerative or low-input farming. An organic farm can be unsustainable as much as a conventional farm can be sustainable. Instead, a sustainable farm produces sufficient amounts of high-quality food, is resource-preserving, environmentally safe and profitable (Reganold et al. 1990), while ensuring a better quality of life for farmers and rural communities. The social aspect is often forgotten in sustainable farming debates in Western societies (Rose and Chilvers 2018).

To assess farm sustainability, a measure that unifies all three pillars is needed. Therefore, farm sustainability is often assessed by a composite indicator. A composite indicator is able to combine all three pillars and their simple indicators into an overarching measure of sustainability. Sustainability indicators provide means to benchmark and compare farms, and offer decision support for farmers and policy makers (Kelly et al. 2018). With sustainability indicators, the heterogeneity of farms and the factors influencing farm sustainability and vice versa can be investigated (Gómez-Limón and Sanchez-Fernandez 2010). The use of composite indicators comes with two main methodological challenges. First, weighting and aggregation of single indicators used to measure the three sustainability pillars is often arbitrary (Greco et al. 2018). The choice of the weighting and aggregation method is decisive for sustainability outcomes, though (Gan et al. 2017). Second, to measure each sustainability pillar with a number of single indicators, a large amount of data is needed. These data are often lacking, not least in the European farming context (Kelly et al. 2018). Especially social indicators are difficult to measure and assess and therefore often disregarded.

1.2 Sustainable Agricultural Innovations

The Organisation for Economic Co-operation and Development (OECD) defines the term 'innovation' as a "new or improved product or process (or combination thereof) that differs significantly from [...] previous products or processes and that has been made available to potential users or brought into use”(OECD/Eurostat 2018, p. 246). The last part of the definition, that the innovation is available to users or brought into use, marks the distinction between innovations and inventions (Fagerberg et al. 2005). Often, ‘technology’ is used interchangeably with innovation. Technologies embody knowledge and are designed material means to ends (Schatzberg and Chicago 2020). However, an innovation is not necessarily a technology (and vice versa), thinking for example of innovative processes (which can be non-technological) and established technologies (which can be no innovations). Yet, novelty does not only imply the creation of completely new products and processes – so-called radical innovations – but also includes small, incremental changes (Garcia and Calantone 2002). An accumulation of incremental changes can have major technological and economic implications in the long run (Smith 2005).

Innovations are embedded in socio-technical environments. Firms usually do not innovate in isolation. Instead, innovation processes are determined by a combination of economic, social, political and organisational factors. Thus, innovation processes require a holistic system approach to the development, diffusion and adoption of innovations (Edquist et al. 2001). The innovation process is not a linear process, but innovations are co-created within a broader system of organisations and institutions (Klerkx et al. 2012). Systems thinking became the most prominent approach also in agricultural innovation research.

Also in Agricultural Innovation Systems (AIS), innovations are the product of socio-technical co-evolutionary processes embedded within complex systems (Klerkx et al. 2012). In AIS, the interaction of actors, such as individual farmers, multinational agricultural firms, farmer organisations, extension services and governmental organisations, within networks is recognised to bring new products, processes and forms of organisation into economic use (OECD 2013a). While agricultural innovation used to be seen as a linear, top-down process in which research and development (R&D) outcomes are passed down to adopters, it is now seen as the result of a non-linear process, characterised by a mix of push and pull factors (Totin et al. 2020).

Sustainable agricultural innovations are novel or improved products or processes that support primary agri-food producers in providing sufficient, healthy and high-quality foods, while staying within planetary boundaries, balancing environmental, economic and social aspects of agri-food production. Sustainable innovations are a means to reduce fertiliser and PPP use, ensure food security and economically viable farming, and minimise nuisance to society and remove health hazards. An example for a sustainable agricultural innovation are microbial applications, which are the subject of this thesis.

Studies on agricultural innovations often investigate one specific technology. The focus on one specific technology provides profound insights into this technology. This has benefits if the goal of one's research is to investigate the uptake or effects of this technology. For instance, in this thesis, a one-technology focus is beneficial to investigate novel microbial applications.

Yet, if the goal is to investigate the overall effect of agricultural innovations on the farm-level, the focus on one single technology or innovation can be misleading. Often, simple proxies, such as investments, patents or the adoption of single technologies, are used to assess how innovative an agricultural firm is (Auci et al. 2020; Diaz-Balteiro et al. 2006). The use of single proxies ignores AIS insights on the importance of collaboration and systemic factors and of innovation development, diffusion and adoption. To cover multi-dimensional innovation processes, composite innovation indicators are used (Carayannis and Provance 2008; Karafillis and Papanagiotou 2011; Läpple et al. 2015; Spielman and Birner 2008). The same methodological challenges regarding weighting and aggregation of single indicators into a composite one apply, as discussed before in the context of sustainability indicators. Thus, a transparent choice of weights and aggregation methods is crucial.

1.3 Innovation Uptake

Recent studies reveal the importance to understand the behavioural factors of adoption of sustainable practices and agricultural innovations (Dessart et al. 2019; Streletskaya et al. 2020). Behavioural factors are psychological factors, such as cognitive, emotional, personal and social processes or stimuli. For instance, it has been found that the perceived usefulness of smart farming technologies is increased by formal sources of information, while being decreased by informal ones (Caffaro et al. 2020), which has an impact on innovation uptake (Toma et al. 2016). Another example for a well-researched behavioural factor is risk aversion distorting rational decision-making. Farmers' risk aversion was found to be one of the hindering factors for sustainable innovation adoption on the farm (Dessart et al. 2019; Isik and Khanna 2003; Liu 2013; Menapace et al. 2013; Trujillo-Barrera et al. 2016). This is especially the case for novel technologies, which are usually assessed as riskier than those currently in use (Bougherara et al. 2017).

Classical examples of interventions to stimulate the uptake of innovations or sustainable practices are the provision of information (Vandevelde et al. 2021), traditional support schemes in the form of subsidies (European Parliament and Nègre 2023), or advisory and extension services (Stræte et al. 2022). Advisory and extension services play an important role as knowledge brokers in the transition of agricultural systems (Cristóvão et al. 2012) and in the diffusion of technological innovations (Eastwood et al. 2017).

It is in the nature of any innovative technology or process that its uptake potential and full effects can only be investigated *ex post*. However, often, technology suppliers and developers need to rely on *ex ante* analyses to support the uptake and to investigate potential effects of their innovations. These *ex ante* analyses are characterised by a lack of data and uncertainties. And still, *ex ante* assessment of agro-environmental innovations is needed to develop more sustainable crop management systems (Blazy et al. 2010). *Ex ante* assessments can be conducted, for example, with simulation models, using expert information as inputs. Thereby, scenarios and circumstances of successful innovation introduction can be understood, and winners and losers identified (Tillie et al. 2014). *Ex ante* assessments may inform the design of intervention policies (Purvis et al. 1995) and allow adjusting the innovations before market entry.

1.4 Problem Statement

Against the backdrop of environmental degradation, climate change, population pressure and supply chain disruptions, our agri-food systems need to become more environmentally friendly while keeping food security and efficiency levels high, and being socially responsible. In short, our agri-food systems need to become more sustainable. On-farm innovations play an important role in the transition towards more sustainable agri-food systems. Further, innovations are assumed to enhance farm efficiency. However, the adoption of sustainable innovations is oftentimes slow.

An example of a potentially sustainable innovation are microbial applications. Microbial applications can serve as an environmentally friendly supplement or substitute for PPP and fertilisers. Previous studies show that microbial applications alleviate abiotic stresses, strengthen crop resilience and support plant growth and quality. To date, little is known about the drivers and barriers of uptake of microbial applications by arable farmers, and how to stimulate the uptake. Uptake decisions are guided by individual behavioural factors and are defined by innovation characteristics. Further, the sustainability and effects of microbial applications on farming sustainability need to be investigated with a transparent and balanced three pillar approach. An *ex ante* examination of uptake factors and effects is constrained by lack of data, but is essential to facilitate the adoption and improve innovation rates. Analysing uptake factors and effects of microbial applications can provide further insights into the uptake and effects of sustainable innovations in general.

1

1.5 Overall Objective and Research Questions

The general objective of this thesis is to investigate the effect of innovation processes on farm performance *ex post*, and of a sustainable innovation on all three sustainability pillars of a Dutch farming system *ex ante*. Further, I investigate behavioural factors for the uptake of sustainable innovations. I focus on European arable farmers and use microbial applications as an example for a sustainable innovation. As agronomists and plant scientists continue to improve the effectiveness of microbial applications, the objective of this thesis is to investigate microbial applications from a social science perspective. To achieve this objective, the following four research questions are addressed.

1. What is the relationship between farmer innovativeness and farm efficiency?

Question one aims to generally assess the effect of innovation processes on farm performance. To address question one, an innovation index to measure innovativeness is computed. Innovativeness is a description of how innovative a farmer is. The index is an expert-weighted Benefit-of-the-Doubt (BoD) composite of technology adoption, development and initiation, investment and continuity. With the use of the composite index, I describe the entire innovation process, in the sense of complex AIS, going beyond a one-dimensional innovation proxy that is tied to a specific innovation. I investigate a longitudinal Farm Accountancy Data Network (FADN) sample of Dutch arable farms.

2. What are farmers' behavioural drivers and barriers to adopt microbial applications in arable agriculture?

Question two aims to identify behavioural factors of the adoption of microbial applications and to recommend tailored interventions. A semi-quantitative online survey among Dutch and German farmers has been conducted to identify drivers and barriers of the adoption of microbial applications. Based on these drivers and barriers, I recommend tailored interventions to support the uptake of microbial applications on arable farms. Drivers and barriers and interventions are identified with the Behaviour Change Wheel (BCW) as an overarching framework (Michie et al. 2014). I use the Capability, Opportunity and Motivation-Behaviour (COM-B) model at the core of the wheel to investigate the drivers and barriers of adopting microbial applications (Gainforth et al. 2016). The outer layers of the BCW are used to device appropriate interventions that stimulate the adoption of microbial applications (West et al. 2020). The methodological contribution of this chapter is the application of the BCW to the context of agricultural innovation.

3. How to stimulate risk-averse farmers to adopt a sustainable innovation?

With the third question, I aim to assess the effect of farmers' risk aversion and the stimulating impact of an informational video on farmers' intention to adopt microbial applications. To address question three, I conducted an online survey, which contains an experiment and a monetarily incentivised Multiple Price List (MPL) lottery game. In the experimental part, a treatment group watched the informational video while the control group received no information. I test whether the treatment group that watched the video is more likely to adopt microbial applications compared to the control group. In the lottery part, both groups played a randomised order of lotteries to elicit the subjects' risk attitudes.

4. How do microbial applications influence the sustainability of Dutch potato production?

Question four aims to assess the potential sustainability of microbial applications *ex ante*. To address the capacity of microbial applications for enhancing the environmental, economic and social sustainability pillars of Dutch potato production, a simulation model is employed. I model a baseline scenario and a microbial application scenario with Monte Carlo simulation, and compare the scenarios using a composite sustainability index. The microbial application scenario is based on data from a Delphi expert elicitation. The results contribute to an understanding of the implicit uncertainty of microbial application effects. Although effect uncertainty is mentioned in other studies, I explicitly quantify it as a core element in my model.

Chapter 2

This Chapter is based on the paper

Tensi, A.F., van der Fels-Klerx, H. J. & Ang, F. (2023). Innovativeness and Technical Efficiency: Evidence from the Dutch Arable Sector. *Submitted to a Journal*.

Innovativeness and Technical Efficiency: Evidence from the Dutch Arable Sector

Abstract We assess the relationship between farmers' innovativeness and farm technical efficiency. Innovativeness – or how innovative a farmer is – is measured with an innovation index. The index is an expert-weighted Benefit-of-the-Doubt composite of technology adoption, development and initiation, investment and continuity. We investigate a longitudinal representative FADN sample of Dutch arable farms. Our empirical findings reveal that innovativeness and efficiency are not related. We reject our pre-registered hypothesis that the relationship between innovativeness and efficiency is inverted U-shaped. Further, we cannot observe a change over time and reject the hypothesis that innovation front-runners become more efficient.

Keywords: Innovativeness, Innovation Index, Efficiency, Benefit-of-the-Doubt

2.1 Introduction

Innovativeness and technical efficiency are both essential for ensuring the long-run economic viability and sustainability of the agricultural sector. Innovativeness refers to how innovative a farmer is, considering the innovation process from development and diffusion to adoption. Technical efficiency measures the extent to which inputs are saved with a given level of production. On the one hand, innovativeness may deter technical efficiency when resources from agricultural production are diverted to the development of innovations or investments associated with adjustment costs in the short run. On the other hand, innovativeness may increase technical efficiency when farmers adopt efficiency-enhancing technologies in the long run. Increasing both innovativeness and efficiency requires an understanding of the synergies and trade-offs between them. Addressing this problem, the current paper assesses the relationship between innovativeness and efficiency in the short run and in the long run.

The concept of innovativeness contrasts with the frequently used crude innovation proxies, such as presence of certain technologies (Karafillis and Papanagiotou 2011) and investment volume (Sauer and Vrolijk 2019). Previous studies focus on investments rather than the underlying innovation processes on farms (Sauer 2017). However, such single indicator proxies do not reflect the complexity of innovation processes and farmers' innovativeness. Innovativeness is difficult to measure because of its complexity and due to the lack of data on the innovation process. Only a few studies focused on measuring the complexity of agricultural innovation (van Galen and Poppe 2013; Läpple et al. 2015). Further, to date, most studies on the relationship between farm innovation and technical efficiency, are confined by a strong focus on the dairy sector (Sauer 2017).

The contribution of this study is threefold. First, going beyond a one-dimensional innovation proxy, we describe the entire innovation process with a multi-dimensional construct (Subramanian 1996).[1] We assess on-farm innovation with an adjusted version of the agricultural innovation index by Läpple et al. (2015). Our composite innovation index consists of five single indicators: i) technology adoption, ii) the nature of the initiator and iii) the developer, iv) investment and v) continuity of innovating. The index allows us to measure a farmer's innovativeness – or how innovative a farmer is – taking multiple dimensions of the innovation process into account. The construct of innovativeness is not tied to a specific innovation and is therefore less situation-specific. Instead, innovativeness explains the agricultural innovation process across several innovations (Midgley and Dowling 1978). Second, while previous research is restricted by limited data, we make use of the rich data set from the Dutch Innovation Monitor. The Innovation Monitor allows

[1] We focus on process innovations only, as these are more prevalent in agriculture than product innovations (Bjerke and Johansson 2022).

us to assess the aforementioned single indicators in depth. Third, in contrast to previous work, we do not focus on the dairy sector, but investigate arable farms. Innovation processes on dairy farms and arable farms differ, which implies different results on efficiency. With this article, we add to the understanding of the effects of innovativeness on farm efficiency of Dutch arable farms.

We aggregate the composite innovation index with the Benefit-of-the-Doubt (BoD) approach based on Cherchye et al. (2007), and assess farmers' efficiencies with Data Envelopment Analysis (DEA) technical efficiency scores. Then, we conduct an econometric analysis and several robustness checks. The main analysis has been pre-registered. We use Dutch Farm Accountancy Data Network (FADN) data, data from the Dutch Innovation Monitor and information from an expert elicitation on Dutch innovations. Data and methods are further described in Section 5.3. In the following section (5.2), we further introduce the concept of innovativeness in agricultural systems and its relationship with efficiency to arrive at two hypotheses.

2.2 Theoretical Background

2.2.1 Innovations and Innovativeness

According to the OECD/Eurostat (2018)'s Oslo Manual, the term 'innovation' is defined as a "new or improved product or process (or combination thereof) that differs significantly from [. . .] previous products or processes and that has been made available to potential users (product) or brought into use (process) [. . .]." (OECD/Eurostat 2018, p. 246). Product innovations refer to a firm's new or improved product that is introduced to the market. Process innovations refer to the way of producing goods and services, and may be technological or organisational (OECD/Eurostat 2018).

Different degrees of innovation process' complexity have been defined. The highest degree of complexity is the innovation system, "consisting of larger number of parts and components, often coming from different disciplines" (OECD et al. 1997, p. 87). In this System of Innovation (SI) approach it is noted that firms usually do not innovate in isolation but that innovation processes are determined by a combination of economic, social, political and organisational factors. The innovation process in SI includes the development, diffusion and adoption of innovations (Edquist 2009). Nowadays, the system view on innovation is prominently used to analyse innovation processes (Zilberman et al. 2022; Kreindler and Young 2014).

Systems thinking has also found its way into agricultural innovation research; also in Agricultural Innovation Systems (AIS), innovation is seen as a co-evolutionary process (Klerkx et al. 2012).

In AIS, the interaction of actors and importance of networks is recognised to bring new products, processes and forms of organisation into economic use (OECD 2013a). These actors are individuals, enterprises and organisations (World Bank 2007, as cited in Klerkx et al. 2012). Examples include individual farmers, multi-national agricultural firms, farmers' organisations, extension services and governmental organisations. While innovation used to be seen as a linear, top-down process in which research and development (R&D) outcomes are passed down to adopters, it is now seen as the result of a non-linear process, characterised by a mix of push and pull factors (Totin et al. 2020). In AIS thinking, this complexity and non-linearity of the innovation process is highlighted (Douthwaite and Hoffecker 2017).

Here, we also adopt a systems view on innovations. We focus on the multi-dimensional innovation development, diffusion and adoption process and consider the role of an individual farmer in these processes. Innovativeness can be defined as the propensity and capacity to innovate (Ettlie et al. 1984; Damanpour 1991). Innovativeness is a trait, an aspect of culture and synonymous with innovation orientation (Garcia and Calantone 2002; Spieth and Schneider 2015). In this study, the construct of innovativeness describes how innovative a farmer is, reflecting multiple dimensions and processes of innovation.

We measure a farmer's innovativeness with an extended innovation index of Läpple et al. (2015). Their index measures agricultural innovation using Ireland as a case study. The Irish composite index consists of three expert-weighted single indicators, namely innovation adoption, acquisition of knowledge and continuous innovation. For the first indicator, five innovative technologies have been selected for three farm systems (i.e. dairy/mixed livestock, cattle/sheep, arable). One of the five technologies is farm system specific, while the other four are identical across the three different systems. Overall, Läpple et al. (2015)'s innovation index reflects the multifaceted agricultural innovation process well. Their acquisition of knowledge indicator is a valuable attempt to represent the network character of the innovation process. Our innovation index differs from that of Läpple et al. (2015) in four ways.

First, we add a single indicator for investments per agricultural area because it is often used as a proxy in literature (Sauer and Latacz-Lohmann 2015; Sauer and Vrolijk 2019; Intellectual Property Organization 2021). Second, we capture the acquisition of knowledge indicator with more detailed proxies, namely the developer and initiator of an innovation, as we have more comprehensive data available. Thereby, we address one of the limitations that was specifically mentioned by Läpple et al. (2015). Third, we employ the BoD approach developed by Cherchye et al. (2006) to assign farm-specific weights to each single indicator which are as optimal as possible for each farm. The BoD approach overcomes the problem of subjective aggregation choices (Mergoni et al. 2022) and integrates aggregation, weighting and index construction (Gan et al. 2017). Last, we extend the index over a number of years and capture continuous innovation to analyse the long-run relationship between innovativeness and efficiency. The missing temporal dimension is another limitation that has been specifically mentioned by the authors of the Irish innovation index.

Even though Sauer and Vrolijk (2019) and Diederen et al. (2003) used the same data to investigate Dutch farm innovation, by comparison, our study portrays innovativeness as a broader set of complementary activities beyond crude proxies and technology adoption. In our study, technology adoption is just one of five single indicators to measure innovativeness. All five single indicators are dimensions of the innovation process and reflect its complexity.

The first single indicator, *adopted technology* – as the ultimate goal of the innovation process – is one of the most used indicators to measure innovation in the agricultural sector (Spielman and Birner 2008). Often, technology use (Ghadim and Pannell 1999; Karafillis and Papanagiotou 2011; Sauer and Zilberman 2012) or adoption frequency (Carmen García-Cortijo et al. 2019; Salavou 2004) are used as proxies to measure innovation.

Through the second and third single indicators *initiator* and *developer*, we are able to capture the idea of AIS that innovation is the result of a collaborative and interactive learning process between multiple diverse actors (Klerkx et al. 2010). With our index, farmers can be coined as highly innovative because they developed an innovation together with partners or because they simply invested and adopted highly innovative technologies. This brings us to the fourth indicator, *investment*. Investment is often used as an innovation proxy as it is easy to measure and an important innovation input (Carayannis and Provance 2008; Sauer 2017; Sauer and Latacz-Lohmann 2015). Further, it is indicative for novel technologies introduced to the farm (Zilberman et al. 2022). Investments and insufficient access to capital are often considered barriers of innovation (Long et al. 2016; Moons et al. 2022).

Finally, the last single indicator, *continuity in innovating*, reflects the importance to continuously innovate (OECD 2013b). The 'temporal conception' of innovativeness, which is a measure of the time of adoption after the product has been introduced to the market, has long been the most common measure of innovativeness (Goldsmith and Foxall 2003). The most prominent theory which uses this conceptualisation of innovativeness is the *Diffusion of Innovation Theory* by Rogers (1983). The Diffusion of Innovation Theory has also been used in Diederen et al. (2003) to measure the innovativeness of farmers. However, such a measure is still focused on single technologies and recognises the adoption process only, leaving out the development and diffusion of innovations. The temporal dimension of adoption as the only measure of innovativeness is insufficient (Goldsmith and Foxall 2003). Yet, it is important to consider the time aspect in the innovation process. According to Subramanian (1996, p. 236), every “valid measure of innovativeness must represent [a] temporal dimension”.

2.2.2 Hypotheses: Innovativeness and Efficiency

Innovation is often seen as the main source of long-run firm growth (Audretsch et al. 2014). Innovations allow farmers to become more efficient in the long run, by saving inputs and reducing environmental impacts in the production process (Balaine et al. 2020). Farmers who do not innovate may lag behind their peers with regards to their production technologies, which may reduce their relative long-run efficiency.

However, in the short run, the relationship between innovativeness and efficiency can be ambiguous. Innovativeness can be a costly trait, requiring resources that could have been allocated to production, which decreases efficiency in the short run. We argue that highly innovative farmers and innovation laggards alike are less efficient than farmers with a medium innovation index in the short run. In other words, the effect of innovativeness on firm performance has diminishing marginal returns (Hervas-Oliver et al. 2018). Accordingly, our **first hypothesis is that the relationship between the innovation index of a farm and the farm’s efficiency can be described with an inverted parabolic shaped curve in the short run**.

According to endogenous growth theories and Schumpeter’s ideas of ’creative destruction’, economic growth is promoted by technological progress. In contrast to neoclassical theories, endogenous growth theories assume that progress comes from within the economic system. Innovations are seen as the starting point and entrepreneurs as driving forces for technological progress and economic growth. We argue that these assumptions hold in the long run (Aghion et al. 2015). Accordingly, our **second hypothesis is that in the long run, innovation frontrunners (highly innovative farmers with high innovation indices) become more efficient or even expand the efficiency frontier**.

2.3 Data and Methods

2.3.1 Data and Descriptive Statistics

In this study, we focus on conventional Dutch arable farms. An arable farm is “an agricultural holding where crop production is the dominant activity, providing at least two-thirds of the production or the business size of an agricultural holding" (Eurostat 2021b). Compared to all other agricultural sectors, the arable sector contributes the most (3.4%) to the added value of the Dutch national economy (Wageningen Economic Research (WEcR) 2022).

The main data source is the Dutch FADN and Innovation Monitor for $2010-2018$. In the Netherlands, both are administered by Wageningen Economic Research (WEcR). The FADN contains data on the economic performance of European farmers. For the Dutch FADN, a statistically representative sample of $180-200$ arable farms is surveyed each year, representing a population of about $7,300-8,500$ arable farmers (Roskam et al. 2022). A professional data collection team conducts face-to-face interviews.

The Innovation Monitor is an annual survey. The complete survey is provided in the supplementary material (in Dutch). among a subset of the FADN farmers. In total, $800-1,000$ farmers complete the Innovation Monitor annually, of which almost 15% are arable farmers. The Innovation Monitor survey consists of three separate parts: product, process and management innovations. The Innovation Monitor panel data can be connected to the FADN panel data through anonymised farm IDs. We combine the two data sources and thereby reduce the data to farms that participated in the Innovation Monitor. Our final sub-sample consists of 902 farmers. The sample is unbalanced. The dataset contains about 30 farms in the years $2010-2013$ and $80-100$ farms in the years $2014-2018$.

Table 2.1 presents the summary statistics and descriptions of variables used in the empirical analysis. WEcR also computes an innovation index dependent on the number of new innovations adopted, which is part of the Innovation Monitor data set. The index, a discrete variable between 1 (laggard) and 4 (innovator), is provided at the bottom of the table and should not be confused with the innovation index computed in this study.

2.3.2 Innovation Index

We measure the abstract construct of 'innovativeness' with a composite index. With complex and multi-dimensional issues, a composite index facilitates interpretation, communication and comparison (Saisana et al. 2005). Constructing composite indices involves a number of subsequent steps, amongst others developing a theoretical framework and selecting variables, normalisation of data, weighting and aggregation, and finally robustness and sensitivity checks (OECD/Eurostat 2018).

Table 2.1: Descriptive statistics, demographics and variables used in empirical analysis.

Statistic	Description	Mean	St. Dev.	Min	Max
Age (in yrs)	Age of the oldest entrepreneur	54.98	9.93	20	81
Labour force (# entrepreneurs)	An entrepreneur is a person who owns the business and also regularly performs labour on the business	1.89	1.08	1	8
Investment (in €)	Total investments	268,082	689,399	0	6,755,869
Variable costs (in €)	Plant related costs, also referred to as variable costs or allocated costs	132,389	141,067	4,363	1,327,446
Fixed costs (in €)	Costs tangible assets, i.e. land, buildings and other durable production assets such as machinery and equipment	200,536	232,424	9,399	2,296,734
Labour (in hrs)	Number of reported hours worked by the entrepreneur, assisting family members, hired workers, permanent staff and volunteers	4,577	3,979	450	40,423
Land (in ha)	Area of cultivated land	100.94	87.54	7.93	859.2
Assets (in €)	Total value of fixed tangible assets	4,673,607	5,080,415	101,959	52,181,459
Revenue (in €)	Total output arable crops, both main and by-product, excludes subsidies	580,493	642,681	26,034	6,100,631
WEcR innovation index	1: no renewal; 2: late adopter; 3: early adopter; 4: innovator	1.4	0.76	1	4

Notes. All values are rounded. This is the summary statistic of all data from all years (2010-2018) from the Innovation Monitor data and FADN.

2.3.2.1 Single Indicators

With the innovation index II_{yf}, we measure innovativeness per year y and farm f. Each term of the summation shown below[2] represents a single indicator. The first term represents whether a certain technology g has been adopted $z_g = [0;1]$, how innovative it is (p_g) and its difficulty of implementation (q_g). The second and third term represent how innovations were developed and who initiated their adoption. The variables x_{df} and z_{rf} are rank aggregations indicating the innovation capacity of the respective developers d and initiators r involved in the innovation process at farm f. The fourth term represents the investment I_{yf} in euro per utilised agricultural area UAA_{yf} per year and farm. The last term represents the continuity of innovation processes. It shows whether renewal took place in the past years $c_{yf} \in (1, Y)$. The single indicators are combined by the BoD approach, which uses linear programming to obtain farm-specific weights w being optimal for each farm. The bonds for these weights are obtained through expert elicitation.

$$II_{yf} = \overbrace{w_{f1} \sum_{g=1}^{G} p_g q_g z_{gyf}}^{\text{technologies adopted}} + \underbrace{w_{f2} x_{df}}_{\text{developer}} + \underbrace{w_{f3} z_{rf}}_{\text{initiator}} + \overbrace{w_{f4} \frac{I_{yf}}{UAAyf}}^{\text{investment per ha}} + \underbrace{w_{f5} \sum_{y=1}^{Y} c_{yf}}_{\text{continuity of innovation}}$$

Fig. 2.1: Annotated Equation 1. Single indicators and aggregation.

Technologies g are selected based on data availability. In the Innovation Monitor, farmers were asked to describe their new or significantly improved process innovations, if they introduced any. This was an open question. We inspect the description of the process innovations, remove all stop-words and retrieve keywords for the most adopted technologies. The ten most adopted technologies from 2010 – 2018 that can be regarded as innovations are provided together with their definition in Table 2.2. These technologies g are incorporated in the first term of the innovation index. Consequently, the list of technologies is dictated by data availability and quality. We exclude technologies such as 'cars' that we do not consider innovative.

Data on the initiators and developers are structured as follows. In the Innovation Monitor, farmers were asked to indicate who developed the innovation and who took the adoption initiative from two lists of possible options. Possible developers d are a 'separate company (partly owned by farmer

[2] Code for annotated LaTeX equations by Sibin Mohan

Table 2.2: Investigated technologies g with definitions.

Technology	Definition	Innovativeness 2014	Innovativeness 2016	Difficulty of Implementation
GPS	Navigation system on tractor, planter, fertiliser spreader, seed drill, self-propelled sprayer/ harvester for efficient field use, straight lines and to prevent overlap	3.8	2.7	2.0
Sensor (and drones)	Sensors for early stage detection of diseases/ weeds or shortage of nutrients/basic elements, determination of biomass of crops/ crop growth, soil sensors; special sensors/ cameras installed on drones to detect e.g. Nitrogen content	4.2	3.9	2.7
Precision Farming	Combining technologies (GPS-systems, drones and sensors) and the information they gather to identify, analyse and manage variability within field for optimum profitability, sustainability and protection of land resource, also to create site specific spraying maps or level controlled drainage	4.1	3.6	2.7
Wingsprayer	For drift reduction	3.9	3.3	1.5
Irrigation systems	/	2.5	2.4	1.7
Non-inversion tillage	Conservation agriculture method	3.7	3.4	2.6
Solar panels	/	2.5	2.1	1.3
Cooling in storage shed	Energy-efficient cooling installation	2.6	2.4	1.7
Storage computer	Climate control to optimise storage conditions, reducing energy use and overall storage costs	2.4	2.2	1.5
Track and Trace	Addition to storage computers, can locate position of products/boxes within storage shed	3.8	3.6	2.1

Notes. 'Innovativeness' (p_g, measured on scale 1-5) and 'Difficulty of Implementation' (q_g, measured on scale 1-3) are mean values from expert evaluation. We adopt the same scales as in the original Irish expert elicitation survey.

himself)', the 'own (agricultural) company', 'mainly others', 'cooperation with other companies' and 'only other companies or institutions'. Initiators are defined as actors supporting and initiating the uptake of an innovation. Possible initiators r are 'advisor', 'customer', 'fellow farmer', the 'own company', 'research institution' or 'supplier'.

We obtain the remaining data for the innovation index from the corresponding FADN data set and the expert elicitation survey. Data on the investment I_{yf} and agricultural area UAA_{yf} come from the corresponding FADN data set. All qualifying weights come from the expert elicitation survey. With the expert elicitation survey, we expect to gain the views of those that are involved in the industry, particularly in relation to the measure of innovativeness in the agricultural sector. The survey has been sent via e-mail to eleven Dutch agriculture and innovation experts and practitioners. To reflect complex AIS, experts with heterogeneous backgrounds have been part of the panel. The identity of the experts is known to the researchers, and the answers are not anonymous. The survey is based on the Irish agri-food innovation survey (Läpple et al. 2015). The complete survey is provided in the supplementary materials. The survey consists of the following three steps.

The expert panel has rated all ten technologies g that were obtained from the Innovation Monitor on an innovation scale from 1 (not innovative at all) to 5 (very innovative) for two different time frames (2014-2016 and 2016-2018) and on an implementation scale from 1 (minor change to the farm) to 3 (major change to the farm). The weights p_g and q_g are the respective averages of the expert ratings and are provided in Table 2.2. The weights p_g and q_g are technology, not farm specific.

Then, the experts have been asked to rank developers d and initiators r with respect to their innovation capacity. To analyse the rankings we follow the Borda rule (OECD/Eurostat 2018): The highest rank depicts the largest innovation capacity and the lowest rank the lowest innovation capacity. We aggregate the ranks with the *RankAggreg* package (Pihur et al. 2020). Rank aggregation is an optimisation problem, and the objective is to find a 'super-list' that is as close as possible to all individually ordered lists. From the developer and initiator super-lists, the developer/initiator with the highest ranking and thus innovation capacity gets the highest value of $x_{df} = 5$ and $z_{rf} = 6$ respectively. The second developer/initiator on the respective super-list is assigned the second highest value, and so on.

Finally, the experts have been asked to express their opinion on how they would weigh the single indicators in a composite innovation index. These expert opinions provide lower and upper bounds for the BoD weights w.

2.3.2.2 Aggregation and Benefit-of-the-Doubt Weighting

Weighting and aggregation have a substantial impact on the final index and are often influenced by subjective perceptions. To remove subjectivity in aggregation, we apply the Benefit-of-the-Doubt (BoD) approach by Cherchye et al. (2007). We aggregate single innovation indicators into a composite index with the constrained BoD approach. The BoD approach is based on an input-oriented DEA model, and the endogenously assigned weights depict each farm in the best possible light relative to the other farms (Mergoni and De Witte 2021). The single indicator values are weighted within an input-oriented DEA optimisation problem that is subject to two constraints. First, the value of the composite index cannot exceed unity. Second, the weights have to be positive and within the bounds (Mergoni et al. 2022). Specifically, for each farm f and year y, we solve the following optimisation problem. Note that we dropped the index y for simplicity.

$$\max \sum_{f=1}^{S} w_{fi} I_{fi} \tag{2.1}$$

$$s.t.: \qquad \sum_{f=1}^{S} w_{fi} I_{fi} \leq 1 \qquad \forall f = 1, \ldots, N \tag{2.2}$$

$$\Theta_i^{\text{lower}} \leq w_{fi} \leq \Theta_i^{\text{upper}} \qquad \forall f = 1, \ldots, N,\ i = 1, \ldots, S \tag{2.3}$$

This is the generalised form of Equation 1 in Figure 2.1. We maximise each farm's composite innovation index II_{yf}, consisting of weights w_{fi} of the i^{th} single indicator of farm f and I_{fi}, the normalised score of the i^{th} single indicator of farm f (Gan et al. 2017; Van Puyenbroeck and Rogge 2017). Each single indicator is normalised with the min-max method ($Y = \frac{X - X_{min}}{X_{range}}$). As the constrained BoD index cannot be computed when one of the single indicators is equal to zero, we normalise the single indicators to a range between one and two ($II \in 1, 2$). We use the build-in *normalise_ci(..., method = 2)* function from the *Compind* package (Vidoli and Fusco 2018). Normalisation is not strictly necessary in the BoD approach but facilitates interpretation of weights (OECD/Eurostat 2018).

Weight restrictions are needed because the extreme weight flexibility of DEA makes the BoD approach highly sensitive to the presence of outliers, and the DEA optimisation process can lead to many zero weights (Vidoli and Mazziotta 2013). Otherwise, some composite indices would become abnormally large and would place farms on the frontier even when the value of all but one single indicators were low (Gonzalez et al. 2018). The bounds Θ in the equation above represent absolute weight restrictions (Allen et al. 1997) and depend on the expert evaluations. The weight bounds are the mean expert evaluations plus/minus one standard deviation ($\pm 1\sigma$).

2.3.3 DEA Efficiency Scores

2

In terms of relative efficiency, a farm is fully efficient if, in comparison to the performance of other farms, i) output production cannot be increased without increasing the level inputs or decreasing outputs (output orientation) or ii) input use cannot be decreased without increasing the level of other inputs or without decreasing outputs (input orientation) (Charnes et al. 1981).

DEA, based on the seminal work by Charnes et al. (1978), is nowadays frequently used to compute technical efficiency.[3] DEA is a linear programme that provides a production possibility surface by 'enveloping' observations with a piece-wise linear frontier (Cooper et al. 2011). The production possibility surface is the technology that transforms a set of inputs into a set of outputs. DEA is a non-parametric method with the benefit that only minimal assumptions are required for its estimation (Coelli et al. 2005).

We conduct an output-oriented, constant-returns-to-scale DEA, formalised as the linear program below. Closely following the expositions of Coelli et al. (2005), the programme is solved for each farm $i \in 1,\ldots,I$ separately so that each farm obtains an efficiency score. The matrices **X** and **Q** consist of all inputs N and outputs M of all firms I.

$$\begin{aligned} & min_{\theta,\lambda} \qquad \theta, \\ s.t. \qquad & -q_i + Q\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{2.4}$$

As in Coelli et al. (2005), θ is a scalar satisfying $\theta \leq 1$. When $\theta = 1$, the farm is technically efficient and on the frontier. Generally, θ represents the efficiency score for the i-th farm. The input vector x_i of the particular farm is contracted as much as possible while still remaining within the feasible input set. The feasible input set is defined by the production possibility surface of the technology. The radial contraction of the input vector (x_i) produces a projected point $(X\lambda, Q\lambda)$ on the production possibility surface. This projected point is a linear combination of the observed data points and λ, a $I x 1$ vector of constants. The constraints in the linear program in Equation 2.4 ensure that this projected point cannot lie outside the production possibility surface (Coelli et al. 2005).

In our model, the input vector (x_i) contains five variables: the total variable/direct costs (in euro), the costs of tangible assets (in euro), the total working hours (in number of hours), the total land use for production (UAA, in hectares) and assets (in euro). The output vector (q_i) consists of a single variable, namely total revenue (in euro). Land is a short-term fixed input and therefore modelled as

[3] See Liu et al. (2013) for a review on DEA literature

negative output. The variable choice is based on Adamie and Hansson (2021). All monetary values are deflated using the respective price indices.

Efficiency scores are computed in two ways. First, all years are pooled and efficiency scores are computed for all years at once. In this case, each farm's performance in a certain year is compared with its performance in the other years and with the performance of all other farms in all years. We call this the *global efficiency* score. Second, efficiency scores are computed on a yearly basis. In this case, a farm's performance in a specific year is compared with the performance of the other farms in the same year. We call this the *local efficiency* score. Efficiency scores are conducted with the *Benchmarking* and the *Compind* packages (Bogetoft and Otto 2010; Vidoli and Fusco 2018). We investigate the differences between the global and the local efficiency scores and their relationship with a correlation analysis.

2.3.4 Analytical Framework: Hypothesis Testing

To test the first hypothesis that the innovation index and the efficiency score relationship can be described with an inverted parabolic curve, we conduct a linear regression analysis. The innovation index is the independent variable, and the efficiency score is the dependent variable. Hypothesis testing is based on a 0.1α error rate, or $p \leq 0.1$. The ordinary least squares (OLS) regression has the following quadratic functional form

$$\theta_{yf} = \beta_0 + \beta_1 II_{yf} + \beta_2 II_{yf}^2 + \epsilon_{yf} \tag{2.5}$$

where θ is the local DEA efficiency score and II_{yf} is the composite innovation index, both of a particular farm f in a certain year y. The βs are the coefficients. Here, β_2 needs to be negative to take on an inverse parabolic shape.

To test the second hypothesis that, in the long term, innovation front-runners become more efficient, we pool the data using global DEA efficiency scores as the dependent variable and time dummies ($t_y \in 1, \ldots, T \; \forall \, T = 9$) to control for year effects. Time t corresponds sequentially to years y; as an example $t_{2010} = 1$. To be in line with the second hypothesis, we expect the coefficients of time t and the interaction effect to be statistically significant and positive.

$$\theta_{yf} = \beta_0 + \beta_1 II_{yf} + \beta_2 II_{yf}^2 + \beta_3 t + \beta_4 II_{yf} \times t + \epsilon_{yf} \tag{2.6}$$

DEA is a nonparametric approach that does not consider noise in a structural way. Banker et al. (2019) show that regressing the contextual variables on the efficiency score is a valid approach if the contextual variables themselves are stochastic. In our application, the (squared) innovation indices contain stochastic information (e.g., investment), but are integrated using a deterministic BoD approach.

2

2.3.5 Robustness Checks and Additional Analyses

We conduct two robustness checks and an additional (non pre-registered) analysis. The first robustness check concerns the aggregation and weighting of the innovation index. In the main approach described above, we use the mean ± 1 standard deviation as the BoD bounds for the weights. As a robustness check, we use the minimum and maximum weight provided by the experts as BoD bounds for each respective single indicator. We call this the *minmax* bound setting method. Further, we aggregate the index with simple average expert weights without the use of the BoD approach. We compare the minmax bounded index and the simple expert weighted index with the main index. We conduct the main analyses with the different indices and compare the final results. The second robustness check concerns the sample. The main sample is unbalanced, i.e. a large majority of farm is not present in all eight years. As a robustness check, we conduct the same analyses with a partially balanced sample, in which farms are present in the sample for at least four out of the nine years. These four years do not need to be consecutive years.

In addition to the pre-registered main analyses, we also conduct an additional, non pre-registered analysis. We conduct both of the regression analyses (Equations 2.5 and 2.6) also with control variables. We use the age of the farmer (in years) and subsidies (in euros) as control variables. We use subsidies as a control variable as Bos et al. (2016) found that subsidised firms are more efficient than those not receiving subsidies. Usually, variables such as farm size or investment are also included as control variables. However, these variables are contained in the DEA efficiency score or the innovation index, which is why they are not treated as control variables.

2.4 Results

2.4.1 Innovativeness

According to the expert panel, the most innovative technologies g are sensors (and drones) and precision farming applications (both with a mean above 4 on a scale from $1-5$). According to the experts, these are also the technologies that impose the greatest change to the farm (both with

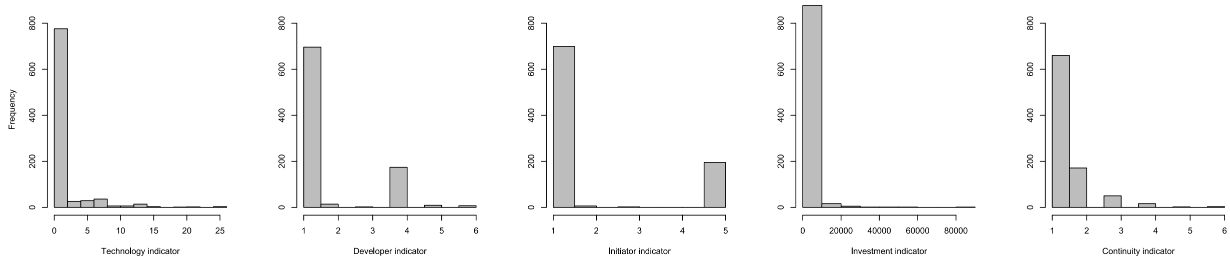

Fig. 2.2: Density plots of each of the five single indicators, before normalisation, transformation and aggregation.

a mean of 2.72 on a scale from $1-3$, see Table 2.2). The rank aggregation of the initiator and developer lists revealed that advisers are the initiators with the largest innovation capacity, followed by suppliers, researchers and customers. The least innovative initiators are farmers themselves and their peers. External companies/institutions and separate enterprises (partly) in the ownership of the farmer are the developers with the largest innovation capacity. The least innovative developers are farmers themselves and cooperations between farmers and others.

According to the experts, the most important single indicator is continuous innovation ($\mu =$ 29.55%), followed by technology adoption ($\mu = 21.6\%$). Investment ($\mu = 17.91\%$) and initiator ($\mu = 19.18\%$) single indicators appear to be almost equally important. The developer indicator is the least important one ($\mu = 12.73\%$).

Figure 2.2 presents a histogram. The histogram shows that the single indicators are right skewed. So, for all single indicators, there is a large number of farmers with a single indicator equal to zero. The single indicators are simple combinations of raw data with expert values. As the expert values are not zero, the skewness of the data is an artefact of the FADN and Innovation Monitor data. For instance, for 776 of the 902 observations, the technology indicator is equal to zero, meaning that the majority of farmers have not adopted any of the ten technologies. Regarding innovation development, 85% of the farmers that provided data (206) indicated that the technology that they have adopted is developed only by others. Only 4% the farmers indicated that they developed the technology themselves and 3% developed it in cooperation with others. The initiative for the uptake however, is mostly taken by the farmers themselves (96%) and only a small minority was nudged by peers (1%) or suppliers (3%).

Summary statistics of the composite innovation index are provided in Table 2.3. Depending on the aggregation method, the innovation indices can be very different. The mean innovation indices are almost identical when aggregated with the BoD approach using minimum and maximum bounds

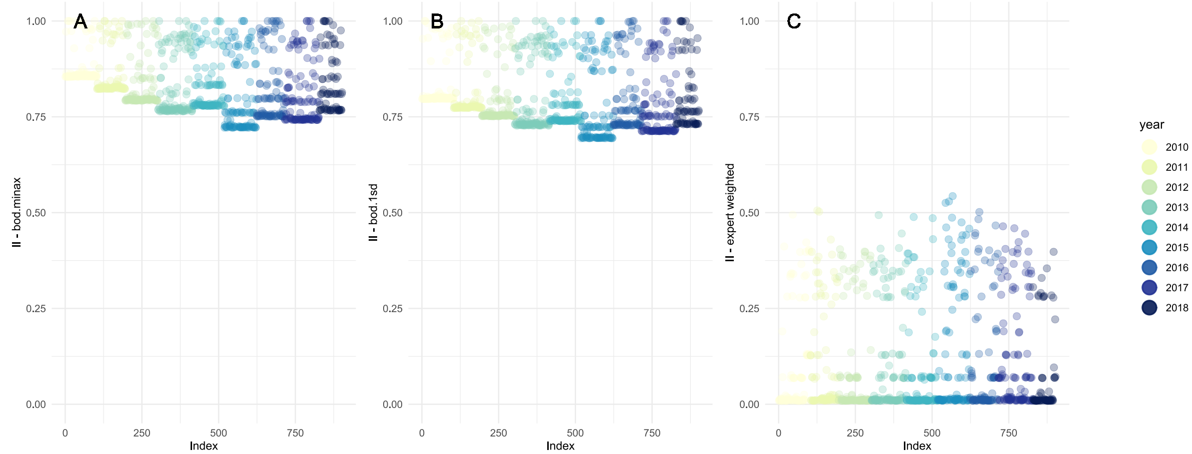

Fig. 2.3: For robustness purposes differently aggregated Innovation Indices: BoD index with minimum and maximum expert weights as bounds (A), with mean $\pm 1SD$ as bounds (B) and simple expert weights aggregated without BoD approach (C).

(called minmax method) and using mean ±1 SD bounds. The mean innovation index over all years is 0.83. The innovation index is stable over time. The mean innovation index, when simply aggregated with expert weights, is 0.1. In Figure 2.3 the similarity between the two BoD-based indices is visualised together with the simple expert weighted index. The BoD-based weighting method produce more favourable indices than the simple expert weighting, which is due to BoD's underlying DEA optimisation technique. A general trend over the years cannot be observed (see Table 2.3 and Figure 2.3).

2.4.2 Efficiency Scores

The mean global efficiency score is 0.54 ($\sigma = 0.16$). In total, 20 farmers (2.22%) can be considered as fully efficient with an efficiency score equal to one. The largest share (30%) of farmers has an efficiency score between 0.4 and 0.5. In other words, the majority of the farms could increase their efficiency. The mean local efficiency score is 0.78 with a standard deviation of 0.16. In total, there are 155 fully efficient farms in the local sample.

In Figure 2.4, the local and global efficiency scores are compared. On the top margin, there are more fully efficient farms in the local sample than in the global sample. This is expected because the local set is a subset of the global set. The higher local efficiency score is indicative for a few efficient farms in some years that set the frontier for all years in the global analysis. The global and

Table 2.3: Summary statistics of Innovation Index.

year	count	mean	standard deviation
2010	103	0.88	0.05
2011	92	0.86	0.06
2012	107	0.83	0.07
2013	113	0.83	0.08
2014	103	0.83	0.07
2015	105	0.8	0.09
2016	92	0.82	0.09
2017	113	0.81	0.08
2018	74	0.84	0.08

Notes. This is the main innovation index computed with the BoD approach and mean ±1 standard deviation bounds.

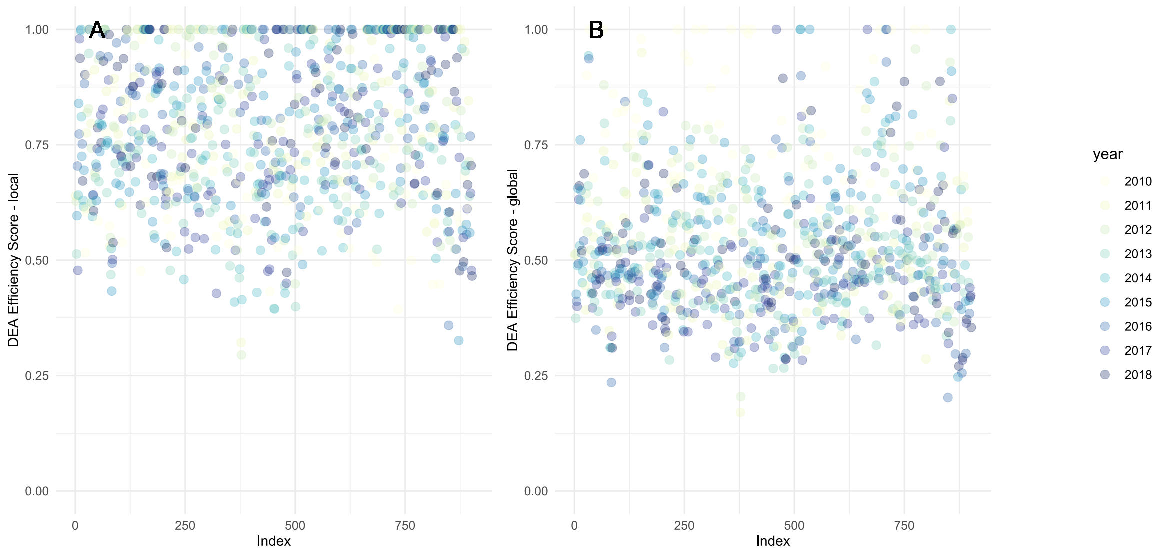

Fig. 2.4: Local (A) and global (B) DEA efficiency scores with year colours.

local efficiency frontiers are presented in Appendix 2.7. The correlation analysis shows that the local and the global efficiency scores are significantly ($p < 0.01$) correlated ($cor = 0.68$). Figure 2.4 also shows that both the local and the global efficiency scores have a limited variation, while the variation of the global score is somewhat larger than of the local score.

Table 2.4 shows that the annual mean efficiency score is stable over time. The number of fully efficient farms varies per year. We found the highest proportion of fully efficient farms in 2018 with 24.32% and the lowest proportion in 2017 with 9.73%.

Table 2.4: Summary statistics of local (1) and global (2) efficiency scores per year, including number and share of fully efficient farms.

year	count	mean		sd	fully efficient			
					number		%	
		(1)	(2)	(1)	(1)	(2)	(1)	(2)
2010	103	0.72	0.72	0.16	13	12	12.62	11.7
2011	92	0.82	0.48	0.15	22	0	23.91	0
2012	107	0.82	0.60	0.15	23	0	21.5	0
2013	113	0.76	0.48	0.16	19	0	16.81	0
2014	103	0.74	0.54	0.17	14	2	13.59	1.94
2015	105	0.79	0.59	0.16	17	3	16.19	2.86
2016	92	0.83	0.49	0.15	18	0	19.57	0
2017	113	0.76	0.47	0.16	11	3	9.73	2.65
2018	74	0.82	0.53	0.16	18	0	24.32	0

2.4.3 Innovativeness and Technical Efficiency

We reject our hypothesis that there is an inverse parabolic relationship between technical efficiency scores and the innovation index based on the results of the OLS regression analysis, see Table 2.5. Since the first coefficient is negative, the coefficients suggest a parabolic relationship rather than an inverse parabolic relationship. We reject the hypothesis even though the innovation index coefficients are statistically significant in the uncontrolled model. The coefficients become insignificant once control variables are introduced. The reason for this change is the presence of auto-correlation, which is revealed through the Durbin-Watson-Test. This means that it is likely that the standard errors are underestimated in the uncontrolled model. The coefficients are more likely to be statistically significant when they are actually not. Therefore, the results of the controlled model are in our opinion more accurate. Further, these findings are robust over different BoD bound settings and index aggregation methods with control variables and on a balanced sample. Overall, the model has a poor fit. The plot in Figure 2.5 visualises the findings.

Table 2.5: Hypothesis 1. Quadratic Regression Model on the relationship between efficiency and innovativeness without and with control variables.

	Dependent variable:	
	local DEA efficiency scores	
	(1)	(2)
	(p)	(p)
Constant	2.689	2.789
	(0.009)	(0.031)
Innovation Index ($\pm 1SD$)	−4.371	−4.543
	(0.063)	(0.121)
Innovation Index^2 ($\pm 1SD$)	2.491	2.580
	(0.063)	(0.120)
Farmer Age (in years)		−0.0004
		(0.535)
Subsidies (in euro)		0.00000
		(0.111)
Observations	902	626
R^2	0.004	0.009
Adjusted R^2	0.002	0.003
Residual Std. Error (df)	0.162 (899)	0.160 (621)
F Statistic (df)	1.743 (2; 899)	1.476 (4; 621)

We also reject the second hypothesis that innovative farmers become more efficient over the years. The results of the second regression analysis are summarised in Table 2.6. In this second model, in which we incorporate time effects, the coefficients suggest an inverse parabolic relationship between the innovation index and efficiency. The second coefficient is negative, while the first one is positive. None of the innovation coefficients are statistically significant. There is no statistically significant interaction effect between the innovation index and time. These findings are robust over different specifications of the regression model and with a balanced sample. The time coefficient is not statistically significant in all models. The results of the robustness checks are included in Appendix 2.7.

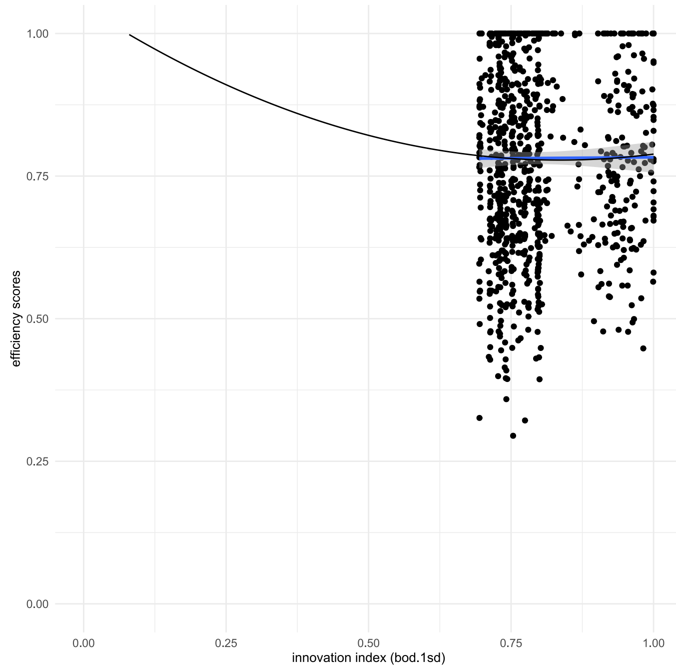

Fig. 2.5: Efficiency scores vs. Innovation Index with fitted regression function.

2.5 Discussion

We do not find a significant relationship between the innovation index and technical efficiency. Farmers with a low innovation index are as likely to be highly efficient as the farmers with a high innovation index. We reject both hypotheses: Innovativeness and efficiency do not stand in an inverted parabolic relationship, and innovative farmers do not catch up with their less innovative, but hypothetically more efficient peers over time. Likewise, Diaz-Balteiro et al. (2006) conclude that there is no significant relationship between innovativeness and efficiency. They have assessed Spain's wood based industry and the relationship between DEA efficiency scores and innovation activities. Their measure of innovation, proxied by the number of patents, product and process innovations, contrasts with our multi-dimensional innovation index. Yet, their methodology and investigated sector resemble our study closely.

In other studies, which differ in terms of methodology and context from our study, a positive relationship between innovativeness and firm performance has been found. For instance, Cruz-Cázares et al. (2013) investigate technological innovation efficiency of Spanish manufacturing firms. They find that firm performance is not driven by simple investment in R&D or uptake of technological innovations but rather by the efficiency of the innovation process. The relationship is

Table 2.6: Hypothesis 2. Quadratic Regression Model on the relationship between efficiency and innovativeness over time without and with control variables.

	Dependent variable:	
	global DEA efficiency scores	
	(1) (p)	(2) (p)
Constant	0.020	0.597
	(0.977)	(0.407)
Innovation Index ($\pm 1SD$)	1.376	0.094
	(0.380)	(0.955)
Innovation Index^2 ($\pm 1SD$)	−0.773	−0.051
	(0.390)	(0.957)
Time t	0.010	0.003
	(0.625)	(0.899)
Farmer Age (in years)		−0.0005
		(0.440)
Subsidies (in euro)		0.00000
		(0.260)
Innovation Index ($\pm 1SD$) x Time	−0.033	−0.022
	(0.202)	(0.42)
Observations	902	626
R^2	0.073	0.069
Adjusted R^2	0.069	0.060
Residual Std. Err(df)	0.153 (897)	0.147(619)
F Statistic (df)	17.705(4; 897)	7.627(6; 619)

moderated by technological intensity and firm size. In our analysis, we do not investigate innovation efficiency, for we do not look at the ratio between innovation inputs and outputs. Auci et al. (2020) use a stochastic frontier analysis to compute technical efficiency scores, and find that innovation positively impacts technical efficiency. However, the authors use the number of patents as the proxy for innovativeness and investigate agricultural firms beyond a certain threshold size, which does not necessarily include farms. In a study on the business performance of Spanish small- and medium-sized enterprises (SME), Expósito and Sanchis-Llopis (2019) distinguish between product and process innovations. They find that product innovations have a significant impact on sales, while process innovations do not enhance business performance.

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There are four possible explanations for rejecting our hypotheses. First, our measure of innovativeness might not be significantly related with technical efficiency because of data limitations. The sample is unbalanced, and a large number of single indicators are zero. Data dictated the technologies that were investigated. Not all of these technologies are efficiency-enhancing. At the same time, the innovation indices have little variation, and many are close to one. Second, our conceptualisation of innovativeness might not be related to managerial capabilities, activities and technologies that enhance farm efficiency. With our conceptualisation of innovativeness, taking on an AIS perspective, we stress the importance of collaboration and continuity beyond simple technology adoption and investment. It seems that some of the – in the AIS-sense – innovative farmers improve the efficiency through these activities while others do not. The reason for this could be related to the last two explanations: Previous studies have found that adoption, development and collaboration alone are not enough. Adoption needs to be accompanied by on-farm learning and education. Technology adoption and innovative behaviour needs to be accompanied by higher quality labour and material intensification (Khafagy and Vigani 2022; Karafillis and Papanagiotou 2011). For instance, Auci et al. (2021) find that knowledge generation processes are the underlying drivers that enhance firm performance when firms adopt certain technologies. To trigger efficiency gains through the adoption of innovations, complementary education is necessary, as exemplified by innovative dairy technologies (Sauer and Latacz-Lohmann 2015). With our innovation index, we do not assess knowledge and capital enhancements that go along with the innovation process. Last, we also do not investigate the institutional and political setting, which is an integral part of AIS. A lack of socio-political support potentially impairs the translation of innovativeness into efficiency gains.

Our empirical results show that the conceptualisation of innovativeness within AIS is expressed well by the innovation index. According to the weighting of the single indicators, continuity in the innovation process and technology adoption are the most important single indicators to reflect innovativeness. This resonates with the conceptualisation of the temporal dimension of innovations (Goldsmith and Foxall 2003; Saisana et al. 2005) and investigation of technology adoption (Carmen García-Cortijo et al. 2019; Karafillis and Papanagiotou 2011). We have been able to show the importance of the temporal dimension through our longitudinal sample and thereby complement the findings of Läpple et al. (2015). Our empirical results also show that a single proxy is not able to reflect the entire innovation process. Especially the investment indicator is insufficient to proxy innovation processes. We find the investment indicator to be as relevant as the initiator indicator and to be third in the ranking only. Similar to Läpple et al. (2015)'s findings, when farmers' innovativeness is measured with our innovation index, farmers do not need large investments to be considered innovative.

There are two interesting findings from the expert elicitation. First, our experts seem to believe that farmers themselves are not able to and/or do not develop or initiate highly innovative technologies themselves. According to the expert elicitation, the least innovative initiators and developers are the farmers themselves and their peers or cooperations. While we adopted an AIS perspective, this finding seems to question the AIS assumption that innovation processes are non-linear (Douthwaite and Hoffecker 2017; Totin et al. 2020). Instead, experts seem to assume that the most innovative solutions are imposed by external parties. Similarly, in a World Bank report, it has been stated in 2006 that "knowledge, information and technology are increasingly generated, diffused and applied through the private sector" (World Bank 2007, p. 3). Second, the weak role of the farmers themselves in the innovation process highlights the need for strong advisory bodies, extension services and external developers. So-called innovation intermediaries, which connect potential collaborators and provide support in finding advice and funding, have been proven as effective in the agricultural sector (Klerkx and Leeuwis 2008). However, advisory services and other intermediaries have to acknowledge farmers' and society's changing needs to be truly effective (Knickel et al. 2009). Further, interdependent actors in an AIS may have divergent or even conflicting interests, which need to be consolidated to not hinder the innovation process (Klerkx et al. 2012).

Despite these valuable insights on the relationship between innovativeness and the nature of innovation processes and its index, there are some limitations to this study. The official definition of AIS also includes institutions and policy makers. However, we use a farmer perspective in which the regulatory system is secondary and do not assess the socio-political context. Furthermore, the innovation index can be easily computed using survey data but the quality of the index depends on the underlying data. The Dutch Innovation Monitor is one of the few rich data sets that considers innovation in a systematic way but is structurally uninformative on which technologies have been adopted. Farmers describe in an open-ended question which technologies they adopted in the past year. We filtered and coded these descriptions and might have thereby introduced inaccuracies to the data. If the survey included a multiple choice list of technologies that are considered innovative and an open question in addition, these inaccuracies could possible be limited. This would eventually improve the quality of the innovation index and corresponding analysis. To go even further, Cristiano and Proietti (2019) suggest to investigate the effect of a specific (cooperative) innovation to farm performance with a participatory method within national Innovation Monitors. Last, a large number of the single indicators is zero because the sample is unbalanced, and not all FADN farmers participate in the innovation monitor.

2

2.6 Conclusion

In this study, we have investigated the relationship between innovativeness and farm technical efficiency. Innovativeness is an AIS-based innovation index measuring how innovative a farmer is. We have tested two hypotheses, namely i) that the relationship between innovativeness and efficiency can be described by an inverted parabolic function and ii) that highly innovative farmers catch up with their highly efficient but less innovative peers over time. We reject both hypotheses. We do not find a statistically significant relationship between innovativeness and efficiency, and there is also no time-trend.

We have two suggestions for further research related to the composition of the innovation index. First, in future research, a single indicator on knowledge generation should be added to the innovation index. According to previous studies, knowledge and material intensification need to be part of the innovation process so that innovation has an effect on efficiency. Our recommendation for future research is to add knowledge generation as a sixth single indicator to the innovation index. Knowledge generation could for example be proxied by time spent in training courses. The relationship between the redefined innovation index and technical efficiency can then be assessed. Second, innovation efficiency and its relationship with technical efficiency could be investigated. Innovation efficiency, as the ratio between innovation inputs and outputs, should have a positive correlation with technical efficiency.

Further, we advise to enhance the Dutch Innovation Monitor in terms of variables investigated and in terms of number of farmers surveyed. We suggest to add an expert-approved multiple choice list of technologies and make the qualitative description optional in case the technology is not part of the list. This extension does not only simplify the data collection process and makes it quicker for farmers to fill in but improves the quality of data and their analyses. Further, we suggest to include all FADN farmers in the sample of the Innovation Monitor.

Our research has several policy implications. First, we find that farmers' innovativeness does not impact farm technical efficiency, likely because of a lack of knowledge intensification. To ensure effects of innovations on economic growth, farm performance and even sustainability of farming, financial and structural R&D support and the strengthening of knowledge systems is important. Second, in this study, we confirm the important role of advisers and external organisations to develop, diffuse and adopt innovation technologies. Policy makers need to focus on strengthening the role of intermediaries, knowledge brokers and advisory services.

2.7 Appendix

Robustness Checks

2

Table 2.77: Robustness Check Hypothesis 1. Quadratic Regression Model with balanced sample (balanced = at least 4 times in the sample) on the relationship between efficiency and innovativeness with and without control variables and with different Innovation Indices.

	Dependent variable:			
	local DEA efficiency score			
	(1)	(2)	(3)	(4)
	(p)	(p)	(p)	(p)
Constant	0.608	−0.180	0.829	0.185
	(0.404)	(0.826)	(0.203)	(0.799)
Innovation Index ($\pm 1SD$)				
			−0.107	1.507
			(0.946)	(0.385)
Innovation Index^2 ($\pm 1SD$)				
			0.058	−0.915
			(0.951)	(0.371)
Innovation Index (minmax)				
	0.412	2.317		
	(0.809)	(0.225)		
Innovation Index^2 (minmax)				
	−0.243	−1.359		
	(0.805)	(0.219)		
Farmer Age (in years)				
		−0.0003		−0.0004
		(0.614)		(0.602)
Subsidies (in euro)				
		0.00000		0.00000
		(0.073)		(0.064)
Observations	752	528	752	528
R^2	0.0001	0.011	0.00003	0.010
Adjusted R^2	−0.003	0.003	−0.003	0.002
Residual Std. Error	0.159	0.155	0.159	0.155
(df)	(749)	(523)	(749)	(523)
F Statistic (df)	0.037	1.390	0.013	1.257
(df)	(2; 749)	(4; 523)	(2; 749)	(4; 523)

Table 2.78: Robustness Check. Quadratic regression model with balanced sample (balanced = at least 4 times in the sample) on the relationship between efficiency and innovativeness, without and with control variables and with different innovation indices.

	Dependent variable:					
	local DEA efficiency score					
	(1)	(2)	(3)	(4)	(5)	(6)
	(p)	(p)	(p)	(p)	(p)	(p)
Constant	0.834	0.371	0.729	0.071	0.772	0.801
	(0.273)	(0.649)	(0.413)	(0.941)	(0.000)	(0.000)
Innovation Index ($\pm 1SD$)						
	−0.030	1.225				
	(0.987)	(0.513)				
Innovation Index^2 ($\pm 1SD$)						
	−0.062	−0.871				
	(0.951)	(0.417)				
Innovation Index (minmax)						
			0.298	1.953		
			(0.881)	(0.353)		
Innovation Index^2 (minmax)						
			−0.293	−1.298		
			(0.791)	(0.269)		
Innoavtion Index (simple expert weights)						
					−0.063	−0.213
					(0.708)	(0.268)
Innovation Index^2 (simple expert weights)						
					0.036	0.066
					(0.930)	(0.880)

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Table 2.78 continued.

	Dependent variable:					
	local DEA efficiency score					
	(1)	(2)	(3)	(4)	(5)	(6)
	(p)	(p)	(p)	(p)	(p)	(p)
Time	−0.018	−0.028	−0.031	−0.036	0.002	0.001
	(0.451)	(0.301)	(0.283)	(0.262)	(0.513)	(0.806)
Farmer Age (in years)						
		−0.0005		−0.0005		−0.0005
		(0.499)		(0.503)		(0.495)
Subsidies		0.00000		0.00000		0.00000
		(0.056)		(0.067)		(0.042)
Innovation Index ($\pm 1SD$) x Time						
	0.026	0.038				
	(0.380)	(0.234)				
Innovation Index (minmax) x Time						
			0.040	0.047		
			(0.234)	(0.207)		
Innovation Index (expert) x Time						
					0.009	0.028
					(0.614)	(0.157)
Observations	752	528	752	528	752	528
R^2	0.003	0.016	0.004	0.018	0.002	0.015
Adjusted R^2	−0.002	0.005	−0.001	0.006	−0.003	0.004
Residual Std. Error	0.159	0.155	0.159	0.155	0.159	0.155
(df)	(747)	(521)	(747)	(521)	(747)	(521)
F Statistic	0.536	1.398	0.795	1.573	0.395	1.349
(df)	(4; 747)	(6; 521)	(4; 747)	(6; 521)	(4; 747)	(6; 521)

Efficiency Frontier

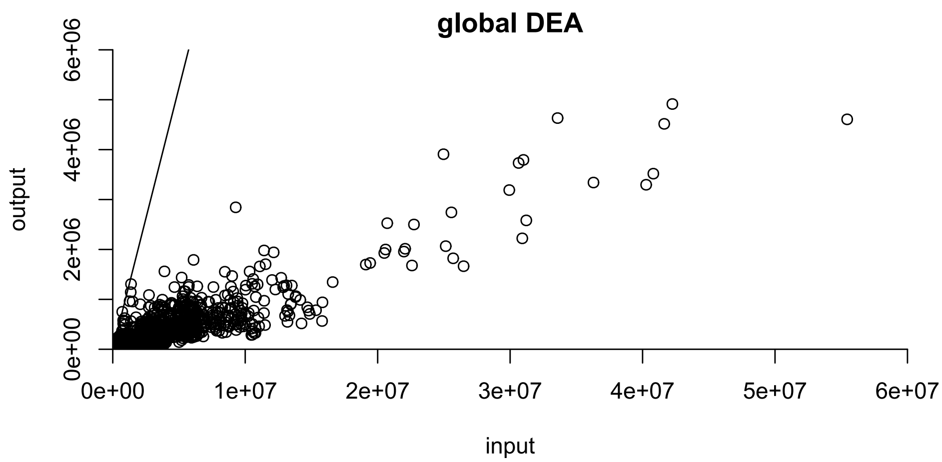

Fig. 2.76: Global efficiency frontier.

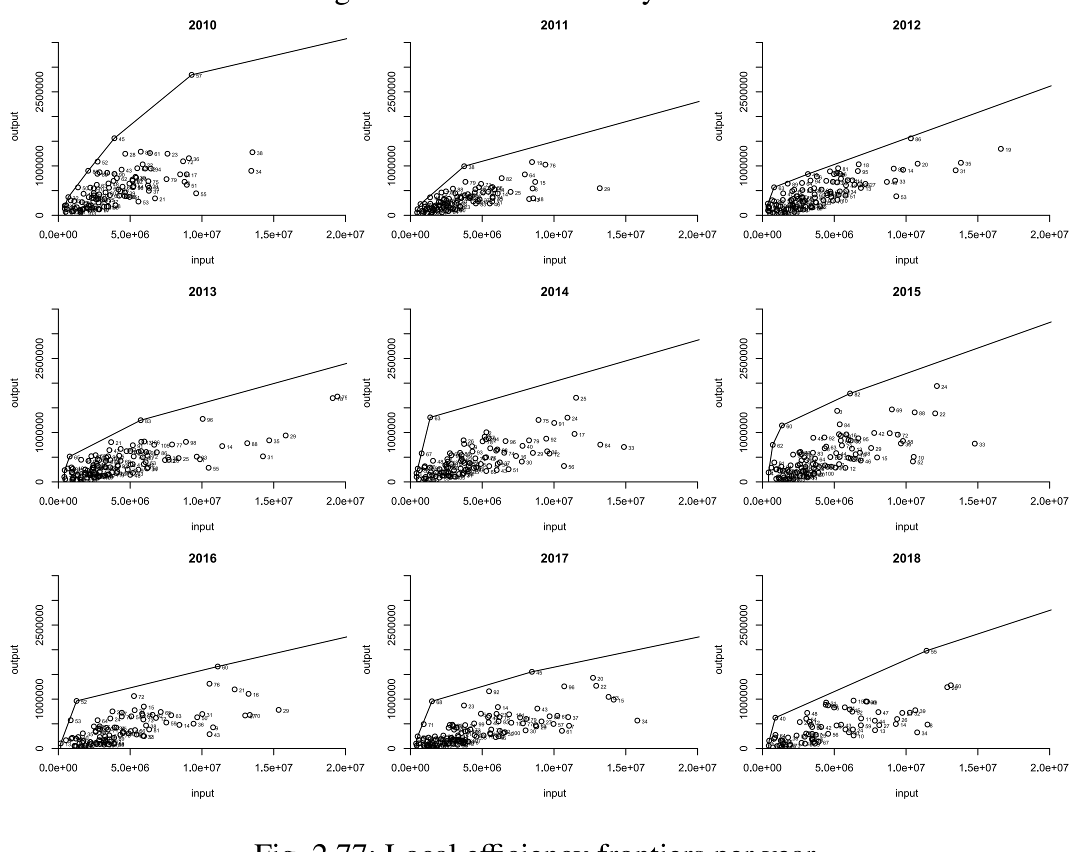

Fig. 2.77: Local efficiency frontiers per year.

Chapter 3

This Chapter is based on the paper

Tensi, A. F., Ang, F., & van der Fels-Klerx, H. J. (2022). Behavioural drivers and barriers for adopting microbial applications in arable farms: Evidence from the Netherlands and Germany. *Technological Forecasting and Social Change, 182*, 121825.

Behavioural Drivers and Barriers for Adopting Microbial Applications in Arable Farms: Evidence from the Netherlands and Germany

Abstract Microbial applications contribute to more sustainable agriculture by stimulating plant growth, increasing resistance to pests and diseases and relieving stresses from climate change. To stimulate the adoption of microbial applications, it is important to understand the underlying reasons for farmers' adoption decision. In this article, we investigate the behavioural drivers and barriers associated with the likelihood to adopt microbial applications. We employ the Behavioural Change Wheel and its capability, opportunity, motivation-behaviour (COM-B) model. Data were collected via an online survey among 196 Dutch and German arable farmers. We find that trust in microbial applications is an important driver and that lack of knowledge and professional support are barriers for the adoption of microbial applications. On this basis, we recommend three interventions: i) norm creation and enablement, ii) education and learning, and iii) trust building by providing incentives. The acceptance and success of a behavioural intervention depends on the choice of the interventionist. For instance, the role of governmental institutions in enforcing the adoption of microbial applications is perceived as problematic by farmers. Instead, farmers expect advisers and farmer organisations to become active in knowledge transmission and field studies.

Keywords: Technology Uptake, Microbial Applications, Behaviour Change Wheel

3.1 Introduction

Farmers and consecutive supply chain actors are faced with the challenge to feed a growing world population with limited resources. This requires a sustainable increase in production whilst decreasing input use. The European Commission (EC) seeks to increase farming sustainability with their Green Deal and Farm to Fork Strategy. The EC's main objective is to reduce chemical and hazardous pesticide use by 50% and fertiliser use by at least 20% by 2030 (EC 2020). In this light, microbial applications in arable farming are important. Microbial applications can decrease the need for plant protection products and fertilisers (Gong et al. 2020; Pertot et al. 2017). Despite recent promising results in the lab and in isolated field trials on the effectiveness of microbial applications, arable farmers are hesitant to adopt these products (Russo et al. 2012).

3

Microbial applications combine different microorganisms such as bacteria, algae, fungi and viruses (Tshikantwa et al. 2018) with complementing traits (Compant et al. 2019). Certain microorganisms living in the root-soil interface improve productivity and quality of crops, suppress plant diseases and control pathogens (Gouda et al. 2018). Microorganisms stimulate the plant's defence mechanisms (Singh and Trivedi 2017). They promote plant growth by stimulating biological nitrogen fixation and nutrient uptake (Wezel et al. 2014), dissolving phosphate and relieving abiotic stresses (de Souza et al. 2015).

Microbial applications can supplement or substitute plant protection products and fertilisers (Elnahal et al. 2022). In the EU, they are currently categorised as plant protection products or biocides (Sundh and Eilenberg 2021), even though they function as biocontrol agents, biostimulants and/or biofertilizers (Marrone 2019). As such, the definition of microbial applications is not clear-cut. Various studies addressed the discrepancies in the registration and regulation of microbial applications in the EU (Frederiks and Wesseler 2019; Köhl et al. 2019). In this study we refer to microbial applications as biopesticides and biofertilizers that are sold as granular or in powder form. Both can be put directly in the soil together with the seeds, dissolved in water to use in irrigation, or suspended in liquid for seed coating.

The low adoption rate of microbial applications calls for an investigation of the underlying reasons to use such innovations in arable farming. Recent reviews reveal the determining role of *behavioural* factors in the adoption of sustainable practices and agricultural innovations (Streletskaya et al. 2020; Dessart et al. 2019). Therefore, this study aims to answer the following research question: "What are farmers' behavioural drivers and barriers to adopt microbial applications in arable agriculture?" We identify the behavioural factors with a semi-quantitative online survey among Dutch and German arable farmers. Based on the identified drivers for and barriers to adoption, we recommend tailored interventions to support the uptake of microbial applications on arable farms. We do so by employing Michie et al. (2014)'s Behaviour Change Wheel (BCW) as an overarching framework. The BCW is a suitable framework to analyse and change behaviour. The BCW is centred around the capability, opportunity and motivation-behaviour (COM-B) model, which identifies sources of a certain behaviour (Gainforth et al. 2016). Based on this "behavioural diagnosis", relevant types of intervention can be identified (West et al. 2020).

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The BCW has thus far mostly been applied to the health and medical context. Examples include prevention behaviour (Gardner et al. 2016; Gould et al. 2017), hygiene (Lydon et al. 2019), medical aid (Barker et al. 2018), physical activity (Webb et al. 2016), and reduction of transmission of the coronavirus disease (COVID-19) (West et al. 2020). A few other applications also focus on the environmental context. Examples include recycling behaviour (Gainforth et al. 2016), a change to energy-related behaviour (Axon et al. 2018) and sustainable food consumption (Hedin et al. 2019). The BCW has rarely been applied in the agricultural context. To the best of our knowledge, there is only one such study on interventions for increasing the frequency of irrigation water sampling and water testing to reduce possible microbiological contamination (Van Asseldonk et al. 2018). The successful introduction of the BCW in these studies suggests it could be useful to study how to stimulate microbial applications in agriculture as well. Furthermore, the BCW has not previously been used to design an online survey. The current article addresses this research gap.

3.2 Theoretical Framework and Hpotheses

3.2.1 The BCW and COM-B Model

The BCW is used to design behavioural change interventions. A behavioural change intervention is a set of activities intended to change behaviour. The behaviour that we intend to change is referred to as the "target behaviour". The BCW assumes that behaviour can be altered through changes of intentions, which depend on attitude and perceptions, and the internal and external environment (Michie et al. 2014). The BCW originated in the health and medical sector. Michie et al. (2009) observed that studies in health and medicine successfully identify patterns that cause unhealthy behaviours. Yet, when it came to designing interventions, little of that knowledge was used. As a result, intervention campaigns did not change the underlying causes of unhealthy behaviours and were often ineffective. Further, effective interventions oftentimes could not be replicated, because they were not supported by theory nor a shared terminology (Michie et al. 2009). Therefore, it was difficult to decipher what makes one intervention effective and another one not (Axon et al. 2018).

Michie et al. (2005) identified the need to create a theoretical framework that analyses both the causes of behaviour and designs interventions targeted at these specific causes.

Similarly, in the agricultural sector, behavioural causes for low adoption rates of technologies or agri-environmental measures have been investigated and effective interventions were sought based on these findings (Streletskaya et al. 2020). Studies on behavioural causes for low adoption rates of technologies or agri-environmental measures often apply Ajzen (1985)'s "Theory of Planned Behaviour" (TPB) (van Dijk et al. 2016). However, TPB is developed specifically for the analysis of behaviour and does not provide a direct link to interventions.

In contrast, the BCW links models of behaviour with interventions (Michie et al. 2014). The wheel has three layers (see 3.7 for a visualisation of the wheel). The core of the wheel is the capability, opportunity and motivation of the target behaviour, the COM-B model. The COM-B model is used to analyse behavioural causes, for example the reasons for resistance to adopt technologies (Barker et al. 2016). The three elements of the COM-B model are defined as follows (Michie et al. 2011b):

- **Capability** represents the **psychological** and **physical** attributes of an individual that enable or facilitate the behaviour. The model distinguishes between knowledge and skills as two separate types of capabilities.
- **Opportunity** describes the environmental factors external to the individual, which enable, facilitate or prevent the behaviour. Environmental factors can be **physical**, such as the lack of tools, or **social**, such as the support by peers. Opportunity and Capability synergistically enable or prevent the behaviour.
- **Motivation** represents the brain processes that energise, demotivate or direct behaviour. Motivation can be **automatic** or **reflective**. Automatic motivations are habitual processes and emotions, while reflective motivations are conscious, analytical decisions.

Figure 3.21 illustrates the interdependence of the elements and their influence on the target behaviour. Following Michie et al. (2011b), we assume that capability and opportunity influence motivation. All three elements are associated with the target behaviour (Lydon et al. 2019). Each element of the COM-B model is directly linked to interventions and policy recommendations. These are placed in the middle and outer layer of the wheel. The link between the COM-B elements and interventions, enables the translation of research on behavioural causes into practice.

3.2.2 Hypotheses

In this article, the COM-B model is used to assess the drivers and barriers to adopt microbial applications. The target behaviour is the uptake of microbial applications on the arable farm. The aim is for microbial applications to (partially) substitute chemical plant protection products and fertilisers. We conceptualise the COM-B elements as behavioural reasons to (not) use microbial applications instead of or in addition to conventional production inputs. We interpret each element as a concrete barrier or driver. The elements are defined as follows: **Psychological capability** represents the farmers' knowledge on microbial applications. High scores in psychological capability mean that farmers want to understand the effects of microbial applications on crops and the environment. **Physical capability** represents the farmers' tools and machinery needed for the application. Examples include spraying devices such as wing sprayers or machinery for seed coating. Overall, capability-related barriers are lack of knowledge, training and machinery. **Automatic motivations** are subconscious beliefs and habitual processes such as trust in microbial applications. **Reflective motivation** represents a conscious judgement on the positive effects of microbial applications. While capabilities and motivations are always farmer-related, opportunities are environmental factors. **Physical opportunities** are places to purchase microbial applications and to get technical support from advisers, farmer organisations or the government. **Social opportunities** are created when peers or family and friends encourage the use of microbial applications.

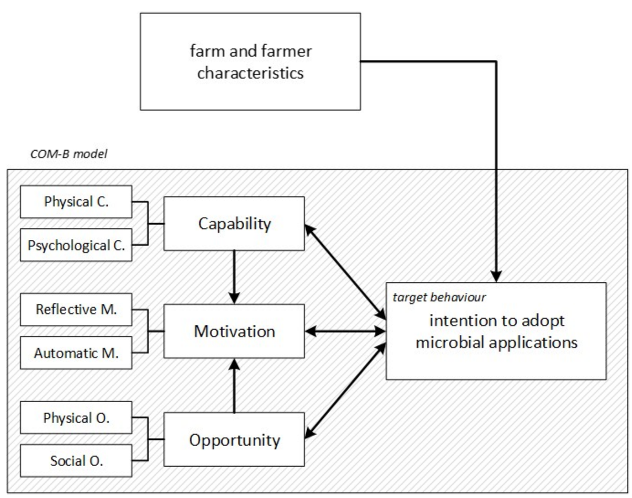

Fig. 3.21: An overview of the relationships between the concepts and the hypotheses to be tested. We extended the base figure of the COM-B model in Michie et al. (2011b, p. 4, Figure 1) by adding the COM-B sub-elements. We also adjusted the figure to our specific context.

We investigate the extent to which each COM-B element is present and related to the adoption of microbial applications. Previous research on the adoption of microbial applications suggests that knowledge, which is reflected in the capability element, lowers the barriers of adoption. Similarly, compatible farm equipment (opportunity) and norm formation (automatic motivation) are drivers for adoption (Parnell et al. 2016; Backer et al. 2018; van Lenteren et al. 2018). We control for farmer characteristics. The only farm characteristic considered is farm type, so whether the farm is an organic or conventional farm. Accordingly, the following pre-registered hypotheses are tested[1]:

1. Farm and farmer characteristics, particularly the year of birth and education,[2] are positively associated with the farmer's likelihood to adopt microbial applications.
2. Capability, Opportunity and Motivation-Behaviour (COM-B) elements are positively associated with the farmers' likelihood to adopt microbial applications.[3]

Figure 3.21 visualises the hypotheses and the interrelation of the elements. The interrelation of the COM-B elements is also tested.

3.3 Data and Methods

3.3.1 Data Collection and Variables

Based on the BCW and the elements described above, we developed a survey. We collected the data via the online survey software Qualtrics from Dutch and German arable farmers in June-July 2020. The survey conditions were approved in advance by the Social Science Ethical Committee of the authors' institution. The survey was designed in English, translated into Dutch and German and back-translated for quality assurance. Native speakers tested the survey in a pilot phase in every language.

To distribute the link and to collect the data, we followed country-specific strategies. In Germany, we contacted about thirty regional farmer organisations across the country to ask for sharing the link to the survey with a short explanation in their next newsletter. The trade magazine *agrarzeitung*

[1] The anonymous link to the project is https://osf.io/ey5sd/?view_only=4c06be3445594768ac20dcbbda6499f0; the link to embargoed registration will be provided in the final publication

[2] Farm size was also pre-registered, but not included in the survey

[3] Please note that in the original pre-registration, we used the phrase 'willingness to adopt' as the term is widely used in the agricultural adoption literature (for instance Möhring and Finger (2022); Teff-Seker et al. (2022); Zeweld et al. (2017). However, in the survey, we asked the farmers to evaluate the 'likelihood' of adoption. To be consistent, we stick to the term 'likelihood'.

published a short note with the link on their website, in their newsletter and their print magazine. Further, the supra-regional organisations *Deutsche Landwirtschafts-Gesellschaft (DLG)* and *Demeter* shared information and the link via e-mail. In the Netherlands, an agency specialised on conducting research among farmers randomly selected 3,000 arable farmers from its database. The farmers were contacted individually via e-mail, describing and inviting them to participate in the research. A reminder e-mail was sent a week later. The sampling design described above warrants representativeness in terms of spatial distribution, management type (conventional vs. organic) and farm size. In the Netherlands, we do not have any insights into the composition of the agency's database, but were assured that the sample resembles the population.

The survey consisted of three parts. First, farmers answered questions on their demographics and characteristics of their farm. Part two concerned general attitudes towards the environment and technologies. In part three, we considered microbial applications.

We elicited initial farmers opinions on and knowledge of microbial applications, followed by an informational video. We included the video in the survey to make sure that all participants had a shared knowledge of microbial applications. The video explains the benefits of microbial applications, how they are applied and stored. The video was developed using input from experts, both in microbiology and in agronomy..[4] After the video, we asked farmers about their general perceptions of microbial applications. We asked whether they already use microbial applications (binary: "yes", "no") or how willing they are to do so. The likelihood is measured by a five-point Likert scale where low values stand for "unlikely", high values for "likely" and three is a neutral response.

Finally, we presented the farmers with 15 statements related to the COM-B elements. For capability- and opportunity-related statements we ask *"When it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to..."*. Automatic motivation-related statements start with *"I trust..."*. Reflective motivation-related statements say *"I am confident that microbial applications..."*. We asked to rate at least three statements for each COM-B element. Participants indicated on a five-point Likert-scale to what extent they agree or disagree with the statements. A score of three is considered a neutral response, higher values reflect agreement, lower values disagreement. An overview of the statements and related COM-B elements is provided in Table 3.31.

[4] The anonymised video file is provided in the following OSF project: https://osf.io/ey5sd/?view_only=4c06be3445594768ac20dcbbda6499f0 The participants had to answer three comprehension questions. The questions were based on the video and tested whether they watched it attentively. There is no evidence of structural misunderstanding or unperceptive watching behaviour.

Table 3.31: Original COM-B elements, sub-elements and variables with question text. Model tested in CFA.

COM-B elements main $\bar{E}_{je}$	sub $\bar{S}_{je}$	Variable x_i	Statement *When it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to...*
Capability	Psychological	Understand	...understand the effect of microbial applications.
		Effect on plants	...know how microbial applications affect crops.
		Effect on soil	...know how microbial applications affect the soil.
	Physical	Training needed	...attend a training to be able to use microbial applications.
		Machinery needed	...acquire necessary machinery to deliver microbial applications.
Opportunity	Physical	Purchase	...know where to purchase microbial applications.
		Support	...get support from advisers/farmer organisations/the government to adopt microbial applications.
	Social	Approval	...get approval from my family/friends and other farmers in my network to adopt microbial applications.
Motivation	Automatic		*I trust...*
		Trust Efficacy	...the efficacy of microbial applications.
		Trust Safety	...the safety of microbial applications.
	Reflective		*I am confident that microbial applications...*
		Soil health	...improve soil health.
		Resistance	...increase crop resistance to extreme weather events (e.g. droughts).
		Plant health	...improve plant health.
		Farmer health	...improve my health.
		Consumer health	...improve consumers' health.

Notes. All COM-B variables are measured on a five-point Likert scale, where high values denote agreement, low values disagreement and 3 a neutral response.

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We also investigated what farmers expect from other actors in the food system. We wanted to know what kind of support is needed to adopt microbial applications. In the survey we asked ' *"what should the following stakeholder do to support your adoption?"*. Farmers provided open answers on advisers, (farmer) organisations, (local) governments and politics. The answers were translated and coded.

After closing the survey, the raw data (N = 415) were cleaned and analysed using R version 3.6.1.[5] Unnecessary (meta) variables were removed and incomplete answers were excluded. The final sample (N = 196) contains only complete responses of Dutch and German farmers that consented to the terms and conditions of the study. Sixteen respondents did not identify themselves as farmers, managers or principal decision makers of an arable farm, and their answers were therefore omitted from the sample.

The representativeness of the sample is limited. First, in Germany, the only sampling option was a voluntary response sample. Thereby, sampling biases might have been introduced. For instance, farmers that are already interested in microbial applications might have been more keen to participate in the survey. Second, the final response rate of completed surveys in the Netherlands is significantly lower than in comparable studies (Hannus et al. 2020; Munz et al. 2020; Reijneveld et al. 2019). Reasons for the low response rate may be the timing of the data collection in summer, the length of the survey, and the absence of financial compensation, all of which have been found to lower the willingness to participate (Pennings et al. 2002). In addition, several replies from farmers indicated a fatigue in participation to (online) studies. Third, since the survey was held on-line, farmers with limited digital literacy skills are automatically excluded. Last, the descriptive statistics show that the sample is better educated than the average farmer population. All in all, these factors decrease the generalisability of our results. Our survey represents the better educated and motivated farmers.

3.3.2 Data Analysis

3.3.2.1 Confirmatory Factor Analysis (CFA)

COM-B elements are latent constructs that cannot be measured directly. Instead, we measure COM-B statement variables. Using the Confirmatory Factor Analysis (CFA), we created COM-B constructs that are linear combinations of the statement variables. The CFA helps us to understand whether the different statements used to elicit one COM-B element indeed belong to the same

[5] The R code will be made available in the online supplementary material and in the OSF project

element. An estimation model determines the appropriate statements (Micheels and Nolan 2016). With a CFA one generally evaluates hypothesised structures of latent constructs. In our case, the hypothesised structure is the allotment of the COM-B statement variables to specific COM-B elements.

Using the CFA, we constructed latent variables. To get from statements via latent variables to individual observations, we used the estimates provided by the CFA: We calculated the individual score of each COM-B element for each participant. With the parameter estimates β_i provided by the CFA, the sub-score S_{je} of each participant j per sub-element e is calculated as follows:

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$$\bar{S}_{je} = \sum_{i=1}^{I} \hat{\beta}_i \, x_i, \tag{3.1}$$

Here, x_i is the observed Likert-scale value for each variable i. The scores of the main COM-B elements E_{je} consist of the sum of its sub-elements. For example, physical and social opportunity are the sub-elements of the main element opportunity.

$$\bar{E}_{je} = \bar{S}_{je_1} + \bar{S}_{je_2} \tag{3.2}$$

This holds for all three COM-B elements and their sub-scales. To test the interrelationship of the COM-B main elements (as depicted in the inner box of Figure 3.21), we conducted an ordinary least square (OLS) regression analysis with the latent motivation element as the dependent variable and opportunity and capability as independent variables. We call this the COM-B OLS regression analysis.

On the statement variables we conducted a preliminary correlation analysis, Kurtosis test and skewness test to identify extreme outliers. Observations with Kurtosis values outside the range of -1 and 1 were considered extreme outliers. Cronbach's alpha of the latent COM-B constructs was compared to its threshold level of 0.7 (Cortina 1993). The model fit was judged based on a set of three fit indices: the model Chi-square test for over-identified models, incremental indices, such as the the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), and the Root Means Square Error of Approximation (RMSEA) as an absolute fit index.

3.3.2.2 Regression Analysis

We used regression analyses to evaluate the factors associated with the uptake of microbial applications. The relationship between COM-B elements and microbial application use offers insights on the drivers and barriers of adoption. The relationship between farm and farmer characteristics should not be interpreted as causal. We distinguish between a usage and a likelihood to adopt model. Usage of and likelihood to adopt microbial applications are dependent variables. The usage model is a binary probit model, the likelihood to adopt model is an ordered probit model. COM-B (sub-)elements and farm characteristics are independent variables. This leaves us with in total six models, belonging to two families, describing usage and likelihood. See Table 3.32 for an overview. The independent variables are i) farm and farmer characteristics (hypothesis 1), ii) the main COM-B elements (hypothesis 2) and iii) control and COM-B variables in one overarching model.

3.3.3 Descriptive Statistics

The final data set contains 133 Dutch (68%) and 63 German (32%) farmers. The response rate with respect to completed surveys is 4.43% in the Netherlands. The response rate is somewhat lower than the response rate of comparable studies, and similar when all initial responses are included. We cannot compute the German response rate due to the voluntary response sampling method. Being predominantly male (93%) and with an average age of 52 ±12 years, our sample provides a reasonable reflection of the farming population with regards to gender and age. According to Eurostat data (Eurostat 2020), 57% of EU farmers are between 40 and 65 years old. In our sample,

Table 3.32: Overview of regression models and their equations.

	usage (y/n)	likelihood (1-5)
demographics	$Pr(a_j=1\|D_{jn})=\phi(\beta_0+\sum_{n=1}^{N}\beta_n D_{jn}+\epsilon_j)$	$Pr[y\leq i\|D_{jn}]=F(\kappa_i-\sum_{n=1}^{N}\beta_n D_{jn}-\epsilon_j)$
	$Pr(a_j=0\|D_{jn})=1-\phi(\beta_0+\sum_{n=1}^{N}\beta_n D_{jn}+\epsilon_j)$	$i=1,...,I$
main COM-B	$Pr(a_j=1\|E_{je})=\phi(\beta_0+\sum_{e=1}^{E}\beta_e E_{je}+\epsilon_j)$	$Pr[y\leq i\|D_{jn}]=F(\kappa_i-\sum_{e=1}^{E}\beta_e E_{je}-\epsilon_j)$
	$Pr(a_j=0\|E_{je})=1-\phi(\beta_0+\sum_{e=1}^{E}\beta_e E_{je}+\epsilon_j)$	$i=1,...,I$
overall model	$Pr(a_j=1\|D_{jn}E_{je})=\phi(\beta_0+\sum_{n=1}^{N}\beta_n D_{jn}+\sum_{e=1}^{E}\beta_e E_{je}+\epsilon_j)$	$Pr[y\leq i\|D_{jn}]=F(\kappa_i-\sum_{n=1}^{N}\beta_n D_{jn}-\sum_{e=1}^{E}\beta_e E_{je}-\epsilon_j)$
	$Pr(a_j=0\|D_{jn}E_{je})=1-\phi(\beta_0+\sum_{n=1}^{N}\beta_n D_{jn}-\sum_{e=1}^{E}\beta_e E_{je}\epsilon_j)$	$i=1,...,I$

Notes. a is the usage boolean variable, 0 denotes "not using microbial applications" and 1 denotes "using microbial applications". A binary probit model is estimated. ϕ denotes a cumulative probability function.
y is the observed likelihood to adopt on an ordered categorical scale from one to five $y \in 1,...,I$ where I denotes the different likelihood levels. Higher values denote a high likelihood to use microbial applications, lower values denote a small likelihood. κ_i are the unknown threshold parameters that divide the slope into I categories. F is a cumulative standard normal distribution. An ordered probit model is estimated.
D_{jn} is a matrix of farm j specific demographic variables n and β_n the associated estimated coefficients. β_0 is the intercept. E_{je} is the farm j specific score of the e^{th} element of the main COM-B elements and β_e the associated coefficients. ϵ_j is the unobserved error term.

almost half of the farmers hold a university degree (46%) and the majority (70%) received a full agricultural education. According to Eurostat (2021a) in total 9.5% of the Dutch and 17% of the German farmers received a full agricultural education in 2016. In comparison to the figures in Table 3.34, our sample is far better educated. This could be attributed to a selection bias and potentially diminishes the representativeness of the final sample.

Table 3.33: Descriptive statistics continuous data.

	Sample			The Netherlands			Germany		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Age	190	51.86	11.52	132	53.57	10.75	58	47.98	12.35
Household size	187	3.51	1.42	128	3.29	1.39	59	4.00	1.39
Expenditure	154	12,999.79	23,940.63	102	13,173.82	25,312.4	52	12,658.40	21,222.75
%for environment	175	32.60	22.69	118	29.67	23.65	57	38.67	19.38
%for profit	171	40.06	23.90	116	35.69	24.39	55	49.27	20.11
%to improve health	150	28.51	23.25	101	28.03	23.96	49	29.49	21.93

Seven percent of the farms in the sample are certified organic. In the EU, in total 7.5% of the farmland is organic (Eurostat 2019). However, in 2018, just five member states accounted for more than half of all organically farmed land, among which Germany (9.1%). According to the most recent (2016) Eurostat data, 3% and 10% of farms in the Netherlands and Germany respectively, were organic with an increasing trend over the last years. In our sample, 5% of the Dutch farms and 11% of the German farms are organic. Thus, our sample resembles the population with regards to the proportion of organic farms. A summary and overview of the descriptive statistics is provided in Tables 3.33 and 3.34. Additional descriptive statistics on farmer attitudes on innovations, the environment, climate change and soil quality and the use of microbial applications, are provided in Appendix 3.7.

3.4 Results

3.4.1 Estimation of COM-B Elements using CFA

The preliminary analysis does not call for exclusion of any variables from the subsequent analysis. Based on the Kurtosis test, COM-B statement variables did not have significant outliers. The

Table 3.34: Descriptive statistics categorical data.

	Sample		The Netherlands		Germany	
Statistic	N	%	N	%	N	%
Country	196		133	68%	63	37%
Male	183	93%	127	95%	56	98%
Education						
Secondary school	19	7%	6	5%	13	21%
High school	86	43%	77	58%	9	14%
Higher education	91	46%	50	38%	41	65%
Agricultural Education						
Basic	19	10%	14	11%	5	8%
Practical	37	19%	27	20%	10	16%
Full	138	70%	90	68%	48	76%
Member organisation	149	76%	101	76%	48	76%
Organic farming	13	7%	6	5%	7	11%
Full-time farmer	63	69%	102	76%	31	50%
Percentage of income from farming						
if not full-time farmer						
0-20%	20	10%	10	8%	10	16%
21-40%	12	6%	5	4%	7	11%
41-60%	16	8%	11	8%	5	8%
61-80%	7	4%	1	1%	6	10%
81-100%	8	4%	4	3%	4	6%

majority of observations were within the acceptable range between -1 and 1. Only a few variables were just outside the range. The skewness test provided a similar picture. Only three of the sixteen COM-B variables have a skewness value of at least one. Most variables were slightly skewed to the right (rather agree than disagree). The Kurtosis and skewness values are provided in 3.73 for completeness. The correlation analysis reveals that the majority of the statement variables have a significant positive correlation with each other (see 3.74).

The p-value of the model's Chi-square is smaller than 0.001, which usually indicates a poor model fit. We ran an exploratory factor analysis (EFA) to make sure that there was no better fitting model for our data. The resulting EFA model Chi-square test is similarly significant. This study intends to test whether the COM-B model is a suitable model in the context of agricultural innovation adoption. Therefore, we stick with the original CFA model. In addition, standardised loadings and other indicators suggest that the model describes the data well (CFI = 0.94, TFI = 0.92, RMSEA = 0.07). Overall, we conclude that there is no better alternative to the proposed COM-B model, but we acknowledge the limitations of the model. The limitations are discussed in Section 5.3.

The Cronbach's alpha values for each of the three COM-B elements and their sub-elements show that the opportunity element does not meet the threshold for internal consistency. This is due to the small number of variables measured to compute the latent factor. We refer to Table 3.41 for estimates, fit indices and Cronbach's alpha values.

The factor loadings are coefficients between the observed COM-B statement variables and the latent COM-B constructs. Based on the factor loadings, we interpret the COM-B elements as follows. The coefficient of physical capability is higher than psychological capability (Table 3.41). Thus, in this context, **capability** refers mainly to physical attributes, such as tools and machinery, enabling or facilitating the uptake of microbial applications. **Opportunities** are to a large extent understood as physical opportunities, namely support provided by the professional network and knowledge of purchase points, and less so as approval from private reference points. **Motivation** is equally described by automatic and reflective motivation. Motivation entails trust in the efficacy and safety. Motivation also includes reflections on the benefits of microbial applications with respect to resistance, soil and plant health.

Table 3.41: Results of the Confirmatory Factor Analysis, including Cronbach's α.

	Ordinary COM-B model	Standardised[a] COM-B model			Cronbach's
	Estimate	Estimate	SE	p	α
Factor Loadings					
Psychological Capability *(C.psy)*					0.90
Understand	1.00	0.68	0.06	0.00	
Effect on plants	1.15	0.81	0.05	0.00	
Effect on soil	1.16	0.79	0.05	0.00	
Physical Capability *(C.phy)*					0.75
Training need	1.00	0.28	0.126	0.02	
Machinery need	1.03	0.25	0.11	0.02	
Funds need	1.16	0.27	0.12	0.02	

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Table 3.41 continued.

	Ordinary COM-B model	Standardised[b] COM-B model			Cronbach's
	Estimate	Estimate	SE	p	α
Automatic Motivation *(M.aut)*					0.72
Efficacy	1.00	0.28	0.16	0.09	
Safety	0.91	0.23	0.13	0.082	
Reflective Motivation *(M.ref)*					0.77
Soil health	1.00	0.46	0.07	0.00	
Plant health	1.09	0.51	0.08	0.00	
Farmer health	0.49	0.20	0.10	0.00	
Consumer health	0.53	0.18	0.05	0.00	
Resistance	1.04	0.48	0.08	0.00	
Physical Opportunity *(O.phy)*					0.56
Support	1.00	0.26	0.12	0.03	
Purchase	1.07	0.29	0.13	0.03	
Social Opportunity *(O.soc)*					/
Approval	1.00	0.84	0.05	0.00	
Capability *(C)*					0.81
C.psy	1.00	0.57	0.10	0.00	
C.phy	1.78	2.41	1.21	0.05	
Motivation *(M)*					0.82
M.aut	1.00	2.78	1.79	0.12	
M.ref	0.89	1.44	0.32	0.00	
Opportunity *(O)*					0.59
O.phy	1.00	2.04	1.06	0.05	
O.soc	1.25	0.63	0.11	0.00	

... continued on the next page.

Table 3.41 continued.

	Ordinary COM-B model	Standardised[b] COM-B model			Cronbach's
	Estimate	Estimate	SE	p	α
Fit Indices					
	Ordinary COM-B model	Standardised COM-B model			
χ^2(df)	184.27(96)	184.27(96)			
p-value	$p < 0.00$	$p < 0.00$			
CFI	0.94	0.94			
TLI	0.92	0.92			
RMSEA	0.07	0.07			

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The COM-B OLS regression results that are presented in the following, deliver seemingly contradictory results to what we see in Figure 3.41. According to the COM-B OLS regression results, capability has a significantly positive effect on motivation ($b = 6.51$, $t(193) = 17.13$, $p < 0.001$) and opportunity has a significantly negative effect on motivation ($b = -3.66$, $t(193) = -14.33$, $p < 0.001$). The adjusted R^2 of the simple regression model is 0.77. While opportunity is negatively associated with motivation in the COM-B OLS regression model, the correlogram in Figure 3.41 visualises that the variables are positively correlated. The reason for this contradiction is the relationship between opportunity and capability. Opportunity and capability are almost perfectly collinear ($r(194) = 0.99$, $p < 0.001$). The Pearson correlation coefficients of capability and opportunity are $r(194) = 0.73$ ($p < 0.001$) and $r(194) = 0.65$ ($p < 0.001$) respectively. This means that the variation of the motivation variable is captured almost entirely by the capability variable and the results are not contradictory. Nonetheless, the findings reveal other issues with the model, which are discussed in Section 5.3. All sub-elements are significantly and highly correlated with the respective main COM-B elements (all with $p < 0.001$). A complete overview of the correlations between all COM-B elements and sub-elements is given in **??**.

3.4.2 Regression Analysis: Drivers and Barriers of Adoption

In total, we estimated six regression models belonging to two different families. We distinguish between a binary probit model, where adoption is the dependent variable, and an ordered probit regression model, where likelihood to adopt is the dependent variable. We run three models in

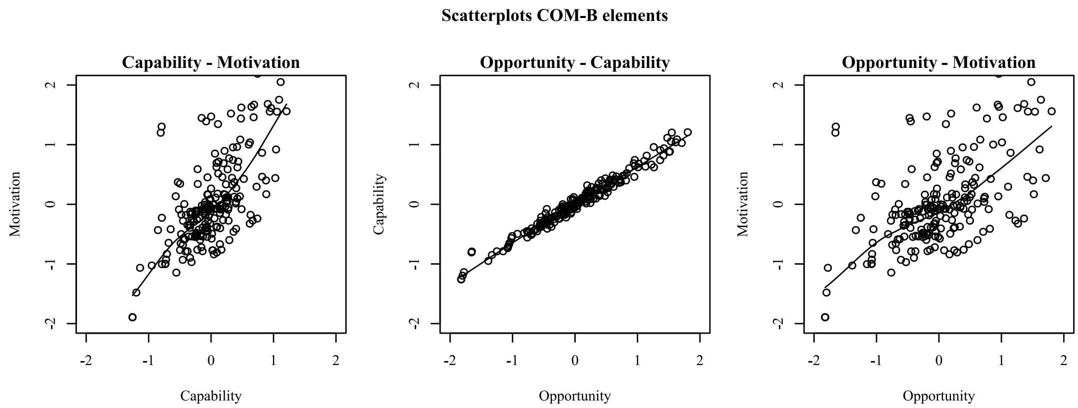

Fig. 3.41: Scatterplots COM-B elements.

each family: i) with the pure demographics, only, ii) the main COM-B elements, and iii) the overall model, in which the first two are combined. In the binary probit model, motivation is significantly and positively associated with the use of microbial applications ($\beta = 1.40, p = 0.00$). Capability and opportunity are significantly associated with the likelihood to adopt (C: $\beta = 10.44, p = 0.02$; O: $\beta = -5.39, p = 0.04$).

The results of the regression analyses on usage and likelihood to adopt microbial applications are presented respectively in Tables 3.42 and 3.43. In the usage model with respect to farmer characteristics, we identify a weakly significant negative association of age ($\beta = -0.04; p = 0.02$) and a positive association of organic farming ($\beta = 1.08, p = 0.09$). Farm management type is not significantly associated with the likelihood to adopt.

To verify any combined effect of farm characteristics and the COM-B model elements, we ran a regression analysis with the COM-B elements and control variables. With regard to usage, when controlling for demographic characteristics, motivation is still highly significant. Additionally, younger farmers are more likely to use microbial applications. In the overarching model, also capability and opportunity become significant on the $\alpha = 0.9$ level. With regards to likelihood, the combined model delivers the same results as in the uncontrolled regression model. None of the farm or farmer characteristics is significantly associated with likelihood to adopt microbial applications. Instead, capability and opportunity jointly affect the likelihood to adopt microbial applications. Capability and Opportunity are significantly associated at the $\alpha = 0.9$ level. Opportunity is negatively associated with the likelihood to adopt microbial applications.

Table 3.42: Results of the ”usage” binary probit regression analysis with different independent variables; Dependent variable: Usage of microbial applications (1: yes, 0: no).

	demographics		COM-B		overall	
	Estimate (SE)	p (t)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Constant	0.52 (1.39)	0.70 (0.38)	-0.75 (0.16)	0.00 (-4.66)	0.56 (1.51)	0.71 (0.37)
Country: The Netherlands	0.18 (0.41)	0.65 (0.45)			0.12 (0.44)	0.78 (0.28)
Gender: Male	0.22 (0.71)	0.75 (0.31)			0.27 (0.79)	0.73 (0.35)
Age	-0.04 (0.02)	0.02 (-2.37)			-0.04 (0.02)	0.03 (-2.20)
Off-farm job: yes	-0.13 (0.39)	0.75 (-0.32)			-0.44 (0.43)	0.31 (-1.03)
Education level						
Higher education	0.21 (0.63)	0.74 (0.34)			0.53 (0.70)	0.45 (0.76)
High school graduate	-0.26 (0.66)	0.69 (-0.40)			0.03 (0.73)	0.97 (0.04)
Agricultural education level						
Practical ag. experience	-0.32 (0.72)	0.66 (-0.44)			-0.59 (0.77)	0.45 (-0.76)
Full ag. training	0.13 (0.60)	0.83 (0.21)			0.22 (0.64)	0.73 (0.34)
Farmer organisation: yes	0.06 (0.42)	0.88 (0.15)			-0.17 (0.45)	0.70 (-0.39)
Organic: Yes	1.08 (0.64)	0.09 (1.67)			0.86 (0.68)	0.21 (1.26)
Household	0.06 (0.12)	0.61 (0.52)			0.01 (0.13)	0.92 (0.10)
Capability			-5.68 (3.97)	0.15 (-1.43)	-8.25 (4.56)	0.07 (-1.81)
Opportunity			3.40 (2.41)	0.16 (1.41)	4.95 (2.76)	0.07 (1.80)
Motivation			1.40 (0.48)	0.00 (2.92)	1.70 (0.55)	0.002 (3.10)

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Table 3.42 continued.

	demographics		COM-B		overall	
	Estimate (SE)	p (t)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Observations	179		195		195	
Null deviance (df)	229.68 (178)		248.24 (194)		229.68 (178)	
Residual deviance (df)	215 (167)		231.32 (191)		198.03 (164)	
AIC	239		239.32		228.03	

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Table 3.43: Results of the ”likelihood to adopt” ordered probit regression analysis with different independent variables; Dependent variable: likelihood to adopt microbial applications (1: very unlikely, 3: neutral, 5: very likely).

	demographics		COM-B		overall	
	Estimate (SE)	p (t)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Constants						
1 | 2	1.68 (1.54)	0.27 (1.09)	-0.66 (0.20)	0.00 (-3.26)	0.47 (1.65)	0.78 (0.28)
2 | 3	3.38 (1.56)	0.03 (2.16)	1.30 (0.23)	0.00 (5.61)	2.63 (1.68)	0.12 (1.56)
3 | 4	4.30 (1.58)	0.01 (2.72)	2.46 (0.33)	0.00 (7.51)	3.86 (1.70)	0.02 (2.27)
4 | 5	5.00 (1.60)	0.001 (3.12)	3.23 (0.43)	0.00 (7.54)	4.78 (1.74)	0.01 (2.75)
Country: The Netherlands	0.27 (0.48)	0.58 (0.56)			0.04 (0.50)	0.94 (0.08)
Gender: Male	1.00 (0.79)	0.21 (1.26)			1.29 (0.90)	0.15 (1.44)
Age	-0.002 (0.02)	0.88 (-0.15)			-0.01 (0.02)	0.74 (-0.33)
Off-farm job: yes	-0.20 (0.43)	0.64 (-0.47)			-0.52 (0.47)	0.27 (-1.10)
Education level						
Higher education	-0.54 (0.71)	0.45 (-0.76)			-0.33 (0.79)	0.67 (-0.42)
High school graduate	-0.37 (0.71)	0.60 (-0.52)			-0.20 (0.80)	0.80 (-0.26)
Agricultural education level						
Practical ag. experience	1.18 (0.74)	0.11 (1.60)			1.23 (0.80)	0.12 (1.54)
Full ag. training	1.29 (0.69)	0.06 (1.87)			1.07 (0.73)	0.14 (1.47)
Farmer organisation: yes	0.45 (0.46)	0.09 (1.70)			0.28 (0.50)	0.59 (0.54)
Organic: Yes	1.26 (0.91)	0.16 (1.40)			0.57 (1.13)	0.62 (0.50)

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Table 3.43 continued.

	demographics		COM-B		overall	
	Estimate (SE)	p (t)	Estimate (SE)	p (t)	Estimate (SE)	p (t)
Household	-0.06 (0.13)	0.67 (-0.43)			-0.19 (0.14)	0.18 (-1.33)
Capability			10.44 (4.44)	0.02 (2.35)	11.37 (5.31)	0.03 (2.14)
Opportunity			-5.39 (2.66)	0.04 (-2.02)	-5.95 (3.16)	0.06 (-1.88)
Motivation			0.03 (0.55)	0.95 (0.06)	0.32 (0.64)	0.61 (0.51)
Observations	117		192		183	
Residual deviance	298.59		295.84		254.62	
AIC	324.59		309.84		290.62	

All in all, we reject the first hypothesis that farm and farmer characteristics are positively associated with the likelihood to adopt microbial applications, but fail to reject the second hypothesis on an association between COM-B model elements and farmer's likelihood to adopt microbial applications. We only find a weak association between the age of the farmer and usage of microbial applications.

3.4.3 Supporting the Uptake of Microbial Applications

Regarding the support desired from others, we find through the qualitative analysis that farmers perceive knowledge transmission and research communication as the two most important tasks. Farmers expect advisers to acquire and disseminate up-to-date knowledge, and provide clear advice. Further, farmers ask for independent, long-term and large-scale field studies and research. Farmers also see their farmer organisations as important accelerators. They expect them to organise knowledge-sharing events. Governments and policy makers should, according to many farmers, not do anything except for providing funds and stimulating research. Example quotes are provided in Table 3.44.

Table 3.44: Example answers provided by farmers on the question:*What should the following stakeholder do to support your adoption?*.

	Advisers	Farmer Organisations	Government	Politics
Knowledge	acquire knowledge; Sharing practical knowledge; spread knowledge	dissemination of knowledge; Facilitating knowledge transfer between colleagues	0.00 knowledge available at local authorities	
Research	Large-scale independent field study; independent research pilot farms (prove what it adds); disseminating practical research data; To come up with results of independent research from the experimental farm	farmers' organisations initiate testing and identify the positive effects of the application on trial fields, etc. when they propagate this, the sector will take up the application	subsidising research and influencing public opinion; stimulating research; research awareness local authorities should also know more about what we do	make money available for tests
Advice		Take note and advise and support whether or not positively		
Information	information on applications, existing products, crop yields and financial consequences	disseminate information, promote		
Other				Allowing producers to have a good range available for the practice

3.5 Discussion

3.5.1 Drivers and Barriers for Adopting Microbial Applications

We estimate two separate models, the binary usage and the ordered likelihood to adopt model, to investigate the behavioural drivers and barriers for adopting microbial applications. The difference between the models is that with the former we investigate farmers that are already using microbials and with the latter we investigate farmers potential likelihood to adopt microbial applications. Thus, the farmers in the two different models have different initial stances towards microbial applications. We find that the drivers and barriers are different in these two models. Our empirical results show that motivation is a behavioural driver in the usage model. In the likelihood to adopt model, opportunity appears to be a behavioural barrier and capability a behavioural driver.

Motivation, which in our context constitutes trust in microbial applications' efficacy and safety, is a crucial driver for microbial application usage. This result from the regression analysis is complemented by the qualitative evaluation of the farmers on what different stakeholders should do to support the uptake: Numerous farmers demand large-scale and long-term field studies to investigate the efficacy of microbial applications. Evidence of a positive effect of microbial application is the basis for trust in the product's efficacy and safety, which is the core of the motivation element. A strong motivation encourages the use of microbial applications.

Opportunity, which constitutes a behavioural barrier to the likelihood to adopt microbial application, is mainly understood in this study as support provided by professional networks and knowledge of purchase points. The results of our regression analysis indicate that when support is needed, the likelihood to adopt microbial applications is negatively affected. The analysis of the qualitative results complements these empirical findings: while the support of knowledgeable advisors and farmer's organisations is desired, governmental and political incentives are perceived questionable by farmers.

Capability, especially in the sense of understanding and knowledge on microbial applications, is a driver to the likelihood to adopt microbial applications. It coincides with "perceived behaviour control" in the "Theory of Planned Behaviour" (Ajzen 1985) and a recent study on the reduction of pesticide use finds that farmers perceive their control over the amount of pesticide use as limited (Bakker et al. 2021).

3.5.2 Intervention Recommendation

One of the BCW's strengths is its direct link of the COM-B drivers and barriers with intervention functions. As a reminder, the BCW consists of three layers. The intervention functions in the second layer of the wheel are methodically connected to the COM-B model at the core of the wheel (Michie et al. 2011b). The BCW shows which COM behavioural deficits can be approach through which intervention functions. In the following, we hypothetically connect our empirical findings on COM-B drivers and barriers to adopt microbial applications to BCW intervention recommendations for farmers.

The first group of interventions is referred to as "build trust, provide incentives". This intervention targets the motivation element of the COM-B model and relates to our qualitative findings. Through large-scale and long-term field studies under realistic conditions, trust can be created. By providing proof that microbial applications work, motivation might be increased and farmers more inclined to use microbial applications on their fields.

The second group of interventions is referred to as “norm creation”. The BCW suggests that opportunity can be achieved through environmental change, restructuring and an enabling environment (Manda et al. 2020; Michie et al. 2011b). A supportive social context encourages the adoption of microbial applications (Michie et al. 2014). Guided by the BCW, we recommend to raise awareness among farmers on microbial applications and their benefits. We recommend to increase general knowledge on the role and importance of microbial applications and convey practical and technical information. For example, it should be clear where to buy microbial applications.

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The last group of interventions, “learning and education”, targets the capability element. Through learning and education, a sense of control can be generated. Here, we do not refer to general schooling or agricultural education, but to specific trainings and information provision on microbial applications. Specific recommendations for training and education interventions can be drawn from the literature on learning and information transmission. Previous research suggests that a combination of extension services and social learning strongly predicts technology adoption (Genius et al. 2014; Yigezu et al. 2018). Social learning refers to the informal exchange of information among peers. Extension services are most effective if there is already a critical mass of adopters. Further, peers can provide first-hand experience with microbial applications (Ojo et al. 2021). Peer-to-peer exchange facilitates social learning and increases the effectiveness of the extension services (Khataza et al. 2018). This group of interventions targets both farmers and extension services and organisations. Our qualitative results show that extension services, advisers and farmer organisations are crucial actors, while there is scepticism towards policy makers and the government as a source of information.

3.5.3 Limitations of the BCW and this Study

The BCW with its COM-B model has rarely been applied in the agricultural context nor has it been used to design an online survey. The current article addressed this research gap and in the following we report key limitations of the BCW and its COM-B model alongside limitations of this study.

First, we find that the BCW step-by-step process as detailed in Michie et al. (2014), is too resource-intensive and difficult to execute in practice. We acknowledge that a two-step process, with an exploratory qualitative study followed by a semi-quantitative study, would be the best way to apply the BCW. However, an iterative process cannot be applied in all cases, as for example study participants might not be available anymore (Gould et al. 2017).

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Second, we find that the BCW cannot be applied seamlessly in a semi-quantitative study. In semi-quantitative online surveys, the BCW's comprehensiveness becomes a weakness. We saw that our survey instrument was tiring for participants which decreased the number of complete responses and data quality. At the same time, a high number of variables usually ensures that all possible drivers and barriers of the adoption are investigated. At least two (preferably three) statement variables per sub-element are needed to get satisfactory information from latent COM-B constructs. In our application, the opportunity element was under-represented. In addition, the physical opportunity element did not explicitly take subsidies into account. In the context of agricultural policy, this is an important element that is missing (Wilson and Marselle 2016). In future research, considerable effort should be made to find just the right amount of questions – not too many to bore participants, and not too little to elicit all aspects necessary.

Further, as latent COM-B elements cannot be observed directly, they need to be translated one-by-one into context-specific variables and questions. In this study, the choice and number of statement variables were the root causes of its key limitation. For instance, one of the main COM-B questions, "when it comes to you personally, what would you need to do to use microbial applications on your farm? I would have to..." might not be applicable to all farmers in the sample. It is crucial that the survey questions appeal to a wide range of farmers with different adoption levels and demographic backgrounds. Further, the answer options might not have been intuitive for or needed re-interpretation by the farmer. This could have introduced variations to the data that cannot be statistically detected. To avoid this kind of ambiguity, validated COM-B survey instruments would be needed (Willmott et al. 2021). In general, the COM-B model might be more suited for qualitative, observational studies unless there are validated, pre-tested survey instruments which can be used reliably in various different contexts.

Third, our results are ambiguous with regard to the COM-B model. On the one hand, the Chi-square results indicate a poor model fit. On the other hand, other fit indices show that the model describes the data well. According to (Xia and Yang 2019), "achieving a set of desired values of RMSEA, CFI, and TLI is one marker showing that the model [is] successful", but still also other modelling options should be explored (p 421). We used EFA to do so. The resulting EFA model did not provide a better alternative in terms of fit. Instead, the ambiguity of our results might be rooted in the chosen statement variables, which further shows the need for a validated survey instrument.

Fourth, the COM-B OLS regression analysis revealed additional limitations of the model. We saw that the model is over-fitted since the variation of the motivation variable is captured almost entirely by the capability variable. Likely, the model does not capture the latent opportunity variable because of the small number of statement variables. Also, per definition of the model, the behavioural intention variable is a confounding variable (as depicted in Figure 3.21) that is not taken into account in our COM-B OLS regression analysis. It might be the case that the behaviour variable explains all or part of the COM elements.

For future research, we want to stress the importance of conciseness, reference to the farming context and clarity of the survey questions. Customisation of survey questions might be as crucial as validation of survey instruments. Despite the limitations of the survey instrument and the previously mentioned limitations of the composition of the sample, our results provide first insights into the behavioural drivers and barriers for the adoption of microbial applications. Our results are not generalisable, but provide a basis for future research, which is discussed in the following concluding section.

3.6 Conclusion and Recommendations

This study investigated the drivers and barriers to adopting microbial applications on Dutch and German arable farms. We hypothesised that farm and farmer characteristics might come into play when making adoption decisions. The results suggest that none of the farm or farmer characteristics are associated with the likelihood of adoption or usage of microbial applications. We find evidence of a positive correlation between the COM-B elements of the BCW and the farmers' likelihood to adopt microbial applications. The results show the behavioural factors serving as drivers for and barriers to the adoption of microbial applications. We applied two distinct models. In the first model, we investigate usage of microbial applications and find that motivation is an important trigger. In the second model, we investigate the likelihood to adopt and find that capability is an important driver and opportunity a barrier.

One of the advantages of the BCW is that COM-B drivers and barriers are directly linked with potential intervention strategies. We linked our empirical findings to BCW-based intervention strategies and recommend three interventions summarised as i) norm creation and enablement, ii) education and learning and iii) building trust by providing incentives. Our qualitative data complement these recommendations: Our results suggest that large-scale and long-term field studies are needed to motivate microbial application adoption. Further, we find that farmers in particular expect advisers to acquire up to date knowledge, to enable dissemination and provide clear advice.

We have four recommendations for further research. First, we recommend to use the findings on the barriers and drivers for the adoption of microbial applications of this study to initiate stakeholder discussions. The aim of these stakeholder discussions should be to verify and eventually adjust or complement the identified drivers and barriers. Thereby, the COM-B model can be adapted to the agricultural context. Second, we recommend to develop and validate COM-B survey elements that are applicable and adaptable to a range of contexts. Currently, it is resource-intensive to use the COM-B model in semi-quantitative online surveys. Pre-defined COM-B statements and a rapid step-by-step process facilitate the use of the BCW. Third, we recommend to investigate whether the suggested intervention strategies increase the adoption of microbial applications. The effectiveness of interventions can be tested in randomised control trials. This study serves as a basis for investigations of the effectiveness of BCW-based interventions. Fourth, we recommend to replicate the study with a large sample, potentially using face-to-face interviews instead of an on-line survey. Such a replication study allows assessing the generalisability of the current study.

3.7 Appendix

The Behaviour Change Wheel

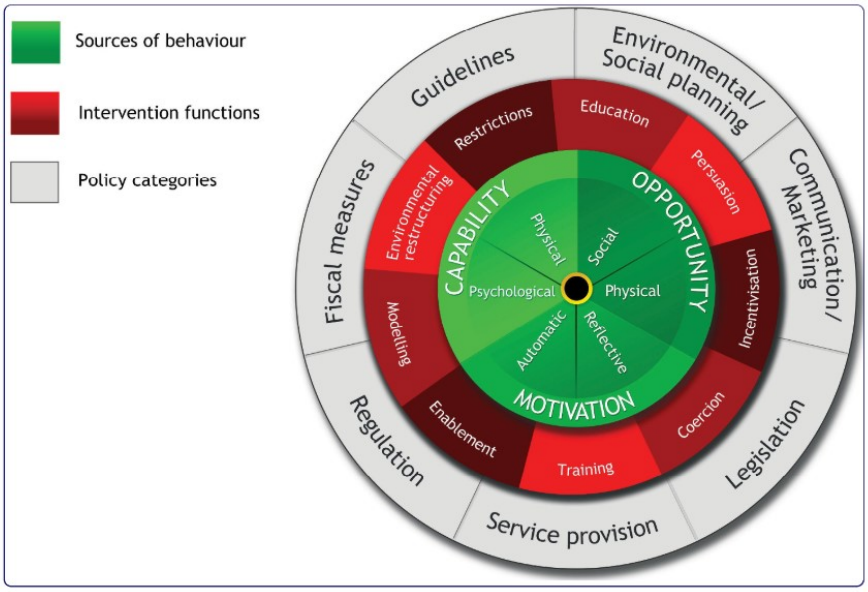

Fig. 3.71: The Behavioural Change Wheel by Michie et al. (2011b).

Summary Statistics of General Attitudes

We characterise our sample in terms of attitudes on innovations, the environment, climate change and soil quality. The farmers are somewhat worried regarding the effects of climate change and neutral towards a potential loss of soil quality. They take on average 3.3 specific measures to protect their soil quality. The most popular measure is to include cover crops in the soil rotation, which is practised by 92% of the Dutch and 80% of the the German farmers in the sample. The farmers do not see themselves as generally open towards innovations or as innovators. We could therefore say that the sample is rather conservative. For a summary of the general attitude variables see Table 3.71.

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Table 3.71: Summary statistics of general attitude variables.

Statistic	N	Median	Mean	SD	Description
Concerns climate[a]	194	2	2.36	1.04	Concerns regarding effects of climate change on farm operations
Concerns soil quality [a]	194	3	2.88	1.15	Concerns regarding long-term soil quality
Number of soil quality measures	196	3	3.28	1.21	Number of measures taking to maintain/improve soil quality
Openness to innovations[b]	195	2	2.83	1.20	Generally open towards adoption of technological innovations on the farm
Innovator [b]	195	2	2.21	1.21	Respondent considers himself an innovator
Technological fix[c]	186	3	2.72	1.27	Confident that environmental problems can be solved in (cost) efficient way with new technologies

Notes.

[a] Standardised such that latent and observed variables have a variance of one [b] Standardised such that latent and observed variables have a variance of one [a] Concern measured on five-point Likert scale, where 3 is considered a neutral response, higher values reflect unconcern, lower values worriedness with respect to the item. [b] Agreement measured on a five-point Likert scale, where 3 is considered a neutral response, higher values reflect agreement and lower values disagreement. [c] Confidence measured on five-point Likert scale, where 3 is considered a neutral response, higher values reflect confidence and lower values doubt.

3

Attitudes towards Microbial Applications

On average, 33% of the participants indicate that they are making use of microbial applications, with almost no difference between the samples from Germany and the Netherlands. Overall, the participants are "somewhat unlikely" to adopt microbial applications (likelihood mean 2.01) despite their "somewhat positive" attitude towards microbial applications (attitude mean 3.74). Participants are rather pessimistic about the costs and benefits in terms of chemical and fertiliser reduction and yield and price premium increases. German farmers are more pessimistic in these domains, except for the price premiums, than Dutch farmers (see Table 3.72 for further details).

Table 3.72: Descriptive statistics of attitudes and perceptions towards microbial applications.

	Sample			The Netherlands			Germany		
Statistic	N	Mean	SD	N	Mean	SD	N	Mean	SD
Usage	195	0.33	0.47	133	0.32	0.47	62	0.35	0.48
Likelihood	128	2.01	1.13	90	2.07	1.19	38	1.87	0.99
Attitude	190	3.74	1.35	130	3.78	1.34	60	3.67	1.37
Costs	192	2.48	1.24	133	2.58	1.22	59	2.27	1.26
Chemicals	192	2.31	1.44	133	2.47	1.53	59	1.93	1.14
Fertilisers	191	2.36	1.42	132	2.58	1.54	59	1.88	0.93
Yield	192	1.73	0.90	133	1.74	0.96	59	1.73	0.74
Price	190	2.28	1.52	132	2.12	1.46	58	2.66	1.62

Kurtosis and skewness

Table 3.73: Kurtosis and skewness test.

COM-B elements main	sub	Variable	Kurtosis	Skewness
Capability	Psychological	Understand	−1.2	−0.2
		Effect on plants	−1.2	−0.2
		Effect on soil	−1.1	−0.3
	Physical	Training needed	−0.6	0.6
		Machinery needed	−1.1	0.4
Opportunity	Physical	Purchase	−0.9	0.5
		Support	−1.1	0.2
	Social	Approval	−1.6	0.0
Motivation	Automatic	Trust Efficacy	1.1	1.1
		Trust Safety	−0.5	0.7
	Reflective	Soil health	−0.2	0.7
		Resistance	0.4	0.8
		Plant health	0.2	0.7
		Farmer health	1.4	1.5
		Consumer health	−0.2	1.1

Correlations COM-B Elements

Table 3.74: Correlation matrix COM-B variables.

	Underst.	Plants	Soil	Train.	Machi.	Funds.	Purch.	Supp.	Approv.	TrustEff.	TrustSaf.	SoilH.	Resist.	PlantH.	FarmerH.	ConsumH.
Understand	1	0.70	0.66	0.39	0.13	0.26	0.20	0.17	0.11	0.18	0.18	0.14	0.21	0.24	0.12	0.11
Effect on plants	0.70	1	0.84	0.29	0.15	0.18	0.18	0.23	0.14	0.09	0.17	0.09	0.14	0.10	0.11	0.11
Effect on soil	0.66	0.84	1	0.25	0.14	0.21	0.10	0.20	0.14	0.10	0.15	0.15	0.17	0.13	0.07	0.13
Training needed	0.39	0.29	0.25	1	0.44	0.45	0.37	0.31	0.26	0.33	0.36	0.24	0.14	0.26	0.16	0.23
Machinery needed	0.13	0.15	0.14	0.44	1	0.44	0.21	0.24	0.35	0.23	0.17	0.16	0.16	0.19	0.23	0.24
Funds needed	0.26	0.18	0.21	0.45	0.44	1	0.36	0.26	0.29	0.36	0.33	0.29	0.25	0.36	0.18	0.32
Purchase	0.20	0.18	0.10	0.37	0.21	0.36	1	0.30	0.15	0.31	0.26	0.17	0.08	0.22	0.08	0.22
Support	0.17	0.23	0.20	0.31	0.24	0.26	0.30	1	0.23	0.22	0.23	0.05	0.02	0.10	0.07	0.13
Approval	0.11	0.14	0.14	0.26	0.35	0.29	0.15	0.23	1	0.15	0.21	0.03	0.06	0.10	0.22	0.27
Trust efficacy	0.18	0.09	0.10	0.33	0.23	0.36	0.31	0.22	0.15	1	0.52	0.51	0.51	0.60	0.23	0.25
Trust safety	0.18	0.17	0.15	0.36	0.17	0.33	0.26	0.23	0.21	0.52	1	0.37	0.35	0.44	0.26	0.24
Soil health	0.14	0.09	0.15	0.24	0.16	0.29	0.17	0.05	0.03	0.51	0.37	1	0.67	0.69	0.20	0.24
Resistance	0.21	0.14	0.17	0.14	0.16	0.25	0.08	0.02	0.06	0.51	0.35	0.67	1	0.75	0.23	0.13
Plant health	0.24	0.10	0.13	0.26	0.19	0.36	0.22	0.10	0.10	0.60	0.44	0.69	0.75	1	0.25	0.20
Farmer health	0.12	0.11	0.07	0.16	0.23	0.18	0.08	0.07	0.22	0.23	0.26	0.20	0.23	0.25	1	0.51
Consumer health	0.11	0.11	0.13	0.23	0.24	0.32	0.22	0.13	0.27	0.25	0.24	0.24	0.13	0.20	0.51	1

Correlations COM-B Sub-Elements

Table 3.75: Correlation matrix of COM-B elements and sub-elements.

	C	M	O	C.psy	C.phy	M.aut	M.ref	O.phy	O.soc
C	1	0.728	0.990	0.562	0.984	0.696	0.584	0.981	0.610
M	0.728	1	0.653	0.326	0.690	0.991	0.915	0.621	0.290
O	0.990	0.653	1	0.589	0.993	0.616	0.510	0.979	0.597
C.psy	0.562	0.326	0.589	1	0.519	0.285	0.290	0.558	0.298
C.phy	0.984	0.690	0.993	0.519	1	0.654	0.547	0.961	0.563
M.aut	0.696	0.991	0.616	0.285	0.654	1	0.863	0.589	0.271
M.ref	0.584	0.915	0.510	0.290	0.547	0.863	1	0.471	0.201
O.phy	0.981	0.621	0.979	0.558	0.961	0.589	0.471	1	0.557
O.soc	0.610	0.290	0.597	0.298	0.563	0.271	0.201	0.557	1

Chapter 4

This Chapter is based on the paper

Tensi, A. F. & Ang, F., (2023). Stimulating Risk-Averse Farmers to Adopt Microbial Applications. *Q Open*.

Stimulating Risk-Averse Farmers to Adopt Microbial Applications

Abstract Increasing agricultural production while decreasing its impact on the environment is a global challenge. Sustainable innovations, such as microbial applications, can play an important role in this light. However, risk-averse farmers are often reluctant to adopt such innovations. In this study, we investigate i) the relationship between risk attitude and farmers' intention to adopt microbial applications and ii) the effectiveness of an informational video to stimulate the adoption. In July 2020, 98 Dutch arable farmers have participated in an online survey with an experiment. In the experiment, half of the farmers have watched an informational video on microbial applications, while the other half was a clean control without receiving information. Then, all farmers are assigned a monetarily incentivised standard Multiple Price List (MPL) and a payoff-varying MPL lottery game to assess the relationship between innovation adoption and risk attitudes. We find evidence that the video has a significant effect on farmers' intention to adopt microbial applications. Further, our results suggest that the intention to use microbial applications can be influenced by farmers' risk attitude.

Keywords. Information Provision, Risk, Probability Weighting, Microbial Applications, Innovation Adoption

4.1 Introduction

The agricultural sector is confronted with a dual, intertwined challenge. Demand for food is increasing because of intensifying population pressure. At the same time, agricultural production creates environmental problems. To tackle this dual challenge, agricultural production needs to increase whilst decreasing the associated environmental impact. In light of this, the widespread adoption of sustainable innovations is essential, but the success of introducing such innovations is limited, as evidenced by precision farming technologies (Hüttel et al. 2020) and crop innovations (Ghadim et al. 2005). Farmers' risk aversion is one of the hindering factors for sustainable innovation adoption on the farm (Dessart et al. 2019; Isik and Khanna 2003; Liu 2013; Menapace et al. 2013; Spiegel et al. 2021; Trujillo-Barrera et al. 2016). This study addresses the research question of how to stimulate risk-averse farmers to adopt a sustainable innovation.

We investigate microbial applications as an example of a sustainable innovation. Microbial applications, which are microbial communities of beneficial, naturally occurring microorganisms, can increase crop productivity whilst reducing environmental pressure. The products are applied to the soil in the area around crop roots as a granulate or as seed coating. The additional workload is limited as the products are applied during the seeding process. Microbial applications fulfil different functions (Philippot et al. 2013). They can increase productivity and the quality of crops, suppress plant diseases, and control pathogens (Singh 2017; Gouda et al. 2018). Microbial applications stimulate biological nitrogen fixation, nutrient uptake (Wezel et al. 2014), phosphate solubilisation and abiotic stress mitigation (de Souza et al. 2015). Despite its benefits, microbial applications are hitherto not widely used in agricultural production.

Evidence shows that visual tools such as videos help to convey complex information (Butler et al. 2020). There have been a few studies investigating the effects of informational videos on the adoption of certain agricultural practices or technologies. For instance, in Vandevelde et al. (2021), an informational video has been used to increase the awareness and adoption of potato quality enhancing practices. In their study, the video indeed increases the probability of adopting the recommended practice. The authors conclude that videos are apt for spreading information on simple, low-cost agricultural practices that have not been widely adopted (Vandevelde et al. 2021). While informational videos might stimulate innovation adoption, farmers' risk aversion has been found to be a hindering factor (Liu 2013). This is especially the case for novel technologies, which are usually assessed as riskier than those currently in use (Bougherara et al. 2017).

While Vandevelde et al. (2021) investigate the effect of the informational video in a developing country on the adoption of an existing farm management practice, we investigate the effect of the informational video on the intended adoption a novel practice *ex ante* and in a European country. We assess the triangular relationship between i) the stimulating impact of an informational video, ii) farmers' risk attitude and iii) their intention to adopt microbial applications.

The impact of the video and farmers' risk attitudes are assessed through an online survey which includes a controlled experiment (see Appendix 4.7 for a schematic representation of the survey and experimental design). A randomly selected half of the participants – in total 98 Dutch arable farmers – watched an informational video, while the other half was in a clean control group. In the video, we explain microbial applications and their benefits. In the second part of the survey, we elicit the risk attitudes of all participants – treatment and control group – using two monetarily incentivised Multiple Price Lists (MPL). We use the Holt and Laury (2002) (H&L) protocol and the payoff-varying MPL by Drichoutis and Lusk (2016) (D&L) to elicit risk and probability weighting function parameters.

This study has been conducted during the COVID-19 pandemic.[1] Starting in late 2019, the pandemic has been unprecedented in our modern world and as such provided a natural experimental setting to researchers. As stated in our AsPredicted.org pre-analysis plan,[2] we wanted to use the novel situation to investigate how the COVID-19 pandemic affects risk attitudes of farmers and the intention to use microbial applications.

Various studies have investigated how detrimental life events and shocks affect individuals' risk attitudes (Andersen et al. 2008; Banks et al. 2020; Bellucci et al. 2020; Cameron and Shah 2015; Cassar et al. 2017). Most recently, it has been found that weather shocks affect farmers' risk aversion (Falco and Vieider 2022). To date at least two excellent studies on the effects of the COVID-19 pandemic on risk attitudes have been published (Drichoutis and Nayga Jr. 2022; Harrison et al. 2022) and numerous studies investigated the effects of the pandemic on agri-food systems and supply chains (Coopmans et al. 2021; Meuwissen et al. 2021; Stephens et al. 2020). Due to financial restrictions we have not been able to collect longitudinal data, which would have enhanced the contribution of this analysis. Further, due to the timing of the survey – just after what we now know marked the first wave in the Netherlands – the variation in our COVID-19 proxies and corresponding conclusions are limited. Therefore, we decided to report the effects of the COVID-19 pandemic on risk attitudes and adoption intentions as secondary analyses. We have

[1] The SARS-CoV-2 (coronavirus) pandemic first emerged in the city of Wuhan, China, at the end of 2019. Causing severe pneumonia, the coronavirus disease (or COVID-19) can be fatal for humans and poses challenges for health care systems all over the world. Being highly transmissible, the coronavirus spread over the world within just a couple of months (Hu et al. 2021). All European countries, including the Netherlands, brought public life to a halt in spring 2020 to limit the spread of the virus.

[2] Pre-registration can be accessed via `https://aspredicted.org/at6w3.pdf`.

kept and analyse the four pre-registered hypotheses, including the ones on COVID-19, but the focus of the discussion is on the remaining hypotheses.

We test four hypotheses. First, we hypothesise that farmers' willingness[3] to adopt microbial applications increases after watching the informational video. Second, we hypothesise that exposure to COVID-19 increases risk aversion among farmers. Our third hypothesis is that risk-averse farmers are less willing to adopt microbial applications. Fourth, we test whether COVID-19 predicts intended use of microbial applications.[4]

4.2 Methodology and Experimental Design

The online experiment consists of three parts.[5] In the first part, we assess farmers' willingness to adopt microbial applications. The second part contains the incentivised MPL. In the last part, we ask questions on the agricultural operations and impact of COVID-19. In the following, we explain each part in detail.

4.2.1 Multiple Price Lists

All subjects are assigned to a randomly ordered sequence of two MPLs. We apply the widely used MPL of Holt and Laury (2002) and the payoff-varying MPL of Drichoutis and Lusk (2016). Despite the widespread use of the H&L MPL for risk elicitation, Herberich and List (2012) and Drichoutis and Lusk (2016) illustrate that it is more suitable for investigating the curvature of the probability weighting function than the curvature of the utility function. The curvature of the utility function signals risk aversion. Both, probability weighting and risk aversion, are a notion of risk. Drichoutis and Lusk (2016) propose a payoff-varying MPL that should be presented to subjects together with the standard H&L MPL to investigate both notions of risk simultaneously and derive more correct risk parameters (Csermely and Rabas 2016). The MPLs differ in whether payoffs or probabilities are fixed. The two MPLs allow us to elicit whether behaviour is driven by actual risk aversion or by a combined effect with over- or under-weighting of extreme events.

[3] Please note that the words intention and willingness are used interchangeably.
[4] In the pre-registration, the informational video is called a "nudge". According to Thaler and Sunstein (2008) a nudge is "any aspect of the choice architecture that alters people's behavio[u]r in a predictable way without forbidding any options or significantly changing their economic incentives". In the current study, the informational video is therefore not regarded as a nudge.
[5] Full instructions are included in the supplementary material.

Table 4.21: H&L multiple price list.

Lottery A				Lottery B				EVA	EVB	Difference	open CRRA interval if subject switches to Lottery B[d]	
p	€	p	€	p	€	p	€	(€)	(€)	(€)		
0.1	20	0.9	16	0.1	38.50	0.9	1	16.40	4.75	11.65	$-\infty$	−1.73
0.2	20	0.8	16	0.2	38.50	0.8	1	16.80	8.50	8.30	−1.73	−0.92
0.3	20	0.7	16	0.3	38.50	0.7	1	17.20	12.25	4.95	−0.92	−0.47
0.4	20	0.6	16	0.4	38.50	0.6	1	17.60	16	1.60	−0.47	−0.13
0.5	20	0.5	16	0.5	38.50	0.5	1	18	19.75	−1.75	−0.13	0.14
0.6	20	0.4	16	0.6	38.50	0.4	1	18.40	23.50	−5.10	0.14	0.40
0.7	20	0.3	16	0.7	38.50	0.3	1	18.80	27.25	−8.45	0.40	0.68
0.8	20	0.2	16	0.8	38.50	0.2	1	19.20	31	−11.80	0.68	0.97
0.9	20	0.1	16	0.9	38.50	0.1	1	19.60	34.75	−15.15	0.97	1.37
1	20	0	16	1	38.50	0	1	20	38.50	−18.50	1.37	$+\infty$

Notes. *p* stands for probability. Last five columns showing expected values and CRRA interval have not been shown to subjects.

[d] assumes Expected Utility Theory; interval is computed by finding the root of the expected utility function using the CRRA specification

In each MPL, the subjects face ten randomly ordered decision situations, in which they choose between two lotteries, A and B. In both MPLs, lottery A is the “safe” lottery compared to lottery B, which is “more risky”. Each decision situation is different and independent of all other decision situations, that is, the decision made in one situation does not affect possible earnings in another.

In the H&L protocol, the payoffs are fixed and probabilities vary in each decision situation. The high payoff in the “risky” lottery is fixed to € 38.50 and to € 20 in the “safe” lottery, whereas the low payoff is set to € 1 and € 16 respectively (see Table 4.21). The probability of the higher payoff increases by 0.1 points in each decision situation.

In the payoff-varying D&L MPL, the probabilities are fixed to 50% in every lottery and the high payoffs differ marginally in each decision situation, the MPL provides insights to ten points on the utility function. The high payoffs in the “safe” lottery vary between € 16.80 and € 24, whereas they vary between € 20.10 and € 47 in the “risky” lottery. In both lotteries, the low payoffs are fixed to € 16 and € 10 respectively. To match potential lottery earnings with the opportunity costs of Dutch arable farmers, we multiply the earnings of the standard MPLs by ten. Details on how we calculated the opportunity costs are provided in Appendix 4.7.

After subjects have gone through all 20 decision situations, we have randomly selected one of them for actual payment. The subjects have been informed in the invitation e-mail that their

Table 4.22: D&L multiple price list: payoff-varying and constant probabilities.

Lottery A				Lottery B				EVA	EVB	Difference	open CRRA interval if subject switches to Lottery B[a]	
p	€	p	€	p	€	p	€	(€)	(€)	(€)		
0.5	16.80	0.5	16	0.5	20.10	0.5	10	16.40	15.05	1.35	$-\infty$	−1.73
0.5	17.60	0.5	16	0.5	21.70	0.5	10	16.80	15.85	0.95	−1.73	−0.92
0.5	18.40	0.5	16	0.5	23.20	0.5	10	17.20	16.60	0.60	−0.92	−0.47
0.5	19.20	0.5	16	0.5	24.80	0.5	10	17.60	17.40	0.20	−0.47	−0.13
0.5	20	0.5	16	0.5	26.50	0.5	10	18	18.25	−0.25	−0.13	0.14
0.5	20.80	0.5	16	0.5	28.60	0.5	10	18.40	19.30	−0.90	0.14	0.40
0.5	21.60	0.5	16	0.5	31.40	0.5	10	18.80	20.70	−1.90	0.40	0.68
0.5	22.40	0.5	16	0.5	35.40	0.5	10	19.20	22.70	−3.50	0.68	0.97
0.5	23.20	0.5	16	0.5	45	0.5	10	19.60	27.50	−7.90	0.97	1.37
0.5	24	0.5	16	0.5	47	0.5	10	20	28.50	−8.50	1.37	$+\infty$

Notes. *p* stands for probability. Last five columns showing expected values and CRRA interval have not been shown to subjects

[a] assumes Expected Utility Theory; interval is computed by finding the root of the expected utility function using the CRRA specification

4

participation is monetarily incentivised based on the answers that they provide. The agency that has handled the recruitment of the farmers has also confidentially administered the payments. All decisions and payments are treated confidentially.

4.2.2 Survey and Experimental Procedure

In mid-July 2020, we have contacted 3,000 Dutch arable farmers via email through a specialised market research agency.[6] Pre-registering sample sizes reduces the degrees of researcher's freedom (Simmons et al. 2021). In our pre-registration, we have indicated to collect 100 observations. To have a safety margin, we have programmed the Qualtrics software such that data collection would close after the 106th complete response. The number of 100 farmers has been dictated by the availability of financial resources to pay out farmers, which is one of the primary reasons for the choice of a sample size (Lakens 2022).

[6] The invitations have been sent out on July 17, 2020 and the survey has been open for about one week until the maximum number has been reached.

The first part of the survey concerns microbial applications and includes the experiment. Half of the subjects are randomly allocated to watch the informational video. The other half of the subjects, the control group, receives no information. The information in the video is based on expert interviews conducted in 2019/2020 with researchers and companies affiliated with microbial applications for the agricultural sector. Later, agricultural microbiologists and agronomists have validated the informational content and graphical representations in the video. We have solicited a company to produce a professional video.[7] After the subjects have watched the video, we ask several comprehension questions to test whether they watched it attentively. We also ask whether the subjects have "ever heard about microbial application in arable farming before the start of this survey". We use the answer to this questions to ensure the clean control. Subjects that answer 'yes' to this question are removed from the control group as a robustness check. Then, we elicit the willingness of the farmer to start or keep using microbial applications (on a scale from 0 to 100). The scale indicates the intention to use microbial applications in the future. In addition, farmers indicate on a scale from 0 to 100 to what extent they trust the efficacy and safety of microbial applications.

Last, we seek information on the agricultural operation and the subject, including information on COVID-19. To assess the impact of COVID-19, we elicit how worried subjects are about the coronavirus (on a scale from one to five) and whether they or someone in their close circle (for example family and friends) has been infected with the virus. We ask three debriefing questions, namely whether the subjects have seen the video or have heard from the project before and whether the instructions have been clear. At the end of the survey, subjects can provide their contact details in a separate form to receive the MPL payment. Subjects explicitly consent and the experimenters use no deception. We have received *ex ante* ethical clearance from the Social Science Ethical Committee for the overall PhD project of the first author, which is funded by SIMBA, on June 12, 2020. The research in the current paper has been approved for *ex post* ethical clearance by the Social Sciences Ethical Committee on February 20, 2023. The online experiment lasts 18 minutes.

4.2.3 Hypothesis Testing

To analyse lottery data and retrieve risk parameters, we investigate the MPLs' switching points. Based on the switching points, we determine observation-specific parameter intervals. From the intervals the respective mid-points are computed with a purpose-built function. We conduct several robustness checks. We use different interval values, namely original values from Holt and Laury

[7] The video is available on YouTube and in the following OSF project: `https://osf.io/7gjwq/`.

(2002) and values from Bellemare (2020).[8] The r values offered by Bellemare and colleagues suggest less extreme risk-loving preferences than the midpoints of the constant relative risk aversion (CRRA) interval in Tables 4.21 and 4.22. Further, we check for an effect of the order of the lotteries, a treatment effect on risk attitude and violations of monotonicity in lottery choices.

We measure the impact of COVID-19 objective data using four different proxies: cumulative positive cases, number of new cases, hospitalisations and deceased. All proxies are normalised at the municipal level to the maximum number per 1,000 inhabitants in the period between the outbreak of COVID-19 in the Netherlands and the start of the experiment.[9] Raw data are retrieved from the RIVM (2021) (*Rijksinstituut voor Volksgezondheid en Milieu*, Dutch National Institute for Public Health and the Environment).[10]

We have pre-registered the analysis for each of the hypotheses as follows. We fail to reject the hypotheses based on a $0.1\,\alpha$ error rate, or $p \leq 0.1$. Generally, two-sample t-tests are used to test whether the means of the control group and the treatment group, two hypothetically independent samples, are significantly different from each other. In fact, this is the classic use of a two-sample t-test (Livingston 2004). We use Welch's t-test instead of Student's t-test. The former is more robust especially when the two samples have different variances and sizes (Delacre et al. 2017; Zimmerman and Zumbo 1993), which is the case here. To test hypothesis 1, we conduct a two-sample t-test to compare the intention of farmers to adopt microbial applications in the video treatment group with the control group. Additionally, we correlate trust in the efficacy and safety of microbial applications with the intention to adopt the products. We conduct another t-test to compare the mean trust in efficacy and safety in the control group and the treatment group. These are potential channels through which adoption could be stimulated, that have not been pre-registered. We did not pre-register a power analysis. In line with (Massfeller et al. 2022), we conduct a power analysis for the t-test on the stimulating effect of the informational video expecting a 10% treatment effect, normalised with a 0.2 standard deviation. With the resulting Cohen's d ($d = 0.5$), a statistical

[8] The following r values from Bellemare (2020) are applied: $r = -0.95$ is assigned to subjects who switch in the first line of the D&L MPL experiment; $r = -0.49$ to subjects who switch in the second line; $r = -0.15$ to subjects who switch in the third; $r = 0.15$ to subjects who switch in the fourth; $r = 0.41$ to subjects who switch in the fifth; $r = 0.68$ to subjects who switch in the sixth; $r = 0.97$ to subjects who switch in the seventh; $r = 1.37$ to subjects who switch in the eighth and $r = 1.50$ to subjects who switch in one of the last two lines.

[9] Normalisation: i) scan the daily COVID-19 figures of the proxies and retrieve the maximum value in the specified time frame; ii) use the maximum values to compute the normalised proxies per 1.000 inhabitants per municipality; iii) connect the respective information to each subject.

[10] RIVM data on COVID-19 are provided on municipality level. We have not directly collected information on the municipality of the subjects. Yet, as subjects indicate the first three digits of their postcode, we are able to match subjects to municipalities using data from the Centraal Bureau voor de Statistiek (2019). Then, we connect the subjects to the RIVM COVID-19 data and inhabitant statistics (Centraal Bureau voor de Statistiek 2020).

significance level of $p = 0.1$ and both samples $N = 50$ the two-sample t-test would reveal a power of 0.79.[11]

Hypothesis 2 is investigated by a correlation analysis with the risk parameters and COVID-19 cases and dismay. In addition, a two-sample t-test investigates the relationship between risk attitude and COVID-19 cases in the close circle. Hypothesis 3 is tested by a correlation analysis in which we test whether there is a significant relationship between risk parameters and the intention to use microbial applications. To complement the two correlation analyses and to test hypothesis 4, we conduct a regression analysis with the dependent variable being the intention to use microbial applications and with the independent variables being risk and probability weighting parameters, a dummy variable for the treatment group, COVID-19 cases and dismay, and several control variables.

4.3 Structural Model and Risk Parameters

Structural modelling is intended to establish which theoretical model maximises the fit with empirical data and can facilitate empirical interpretation (Harrison and Ross 2018). We compare expected utility theory (EUT) and rank dependent utility (RDU). We do not include cumulative prospect theory (CPT) by Tversky and Kahneman (1992) for two conceptual reasons. First, our MPLs do not allow to investigate CPT's loss aversion, since the payoffs are all positive. Second, we focus on investigating risk attitudes and their effect on technology adoption. Even though risk aversion and loss aversion are closely connected, we do not want to investigate loss aversion. CPT usually outperforms EUT in terms of data fit and actual behaviour elicited in the lab (Schmidt and Traub 2002; Tversky and Kahneman 1991). However, there are also studies that question the importance of loss aversion (Gal and Rucker 2018). Other studies imply that CPT's dominance can be attributed to probability weighting rather than to loss aversion. RDU is in this light preferable to CPT (Harrison and Ross 2017).

We have planned to estimate the curvature of the utility and probability weighting function with the data from the MPLs, and to estimate the function parameters to determine observation specific risk attitudes. The approach is described in further detail in Andersen et al. (2008) and the supplementary material of Harrison and Rutström (2008). We have largely followed Drichoutis and Lusk (2016). In the following, we describe the models and maximum likelihood estimation (MLE) procedure, why the MLE did not converge and general problems with structural modelling.

[11] computed with the pwr R package (Champely 2020)

As a basis for both models, we assume that subjects maximise utility and are risk-averse. Constant relative risk aversion (CRRA) is formalised as

$$U(x) = \frac{x^{(1-r)}}{(1-r)}, \tag{4.1}$$

where r is the CRRA coefficient and x the possible payoff in the respective MPL decision situation as fixed by the experimenter. If $r = 0$, there is risk neutrality, which means that the utility function becomes $U(x) = x$. If $r > 0$, the payoff x is discounted by the CRRA coefficient and utility decreases, which implies risk aversion. The opposite occurs if $r < 0$, in which case the subject is risk-loving. The expected utility EU of a lottery i is then expressed as

$$EU_i = \sum_{k=1}^{K} (p_k \times U_k), \tag{4.2}$$

where k denotes the possible outcomes of a lottery ($K = 2$) and p_k the probability of outcome k. The difference in expected utilities is $\Delta EU = EU_i - EU_j$. Subjects switch to lottery B when $\Delta EU = EU_A - EU_B + \epsilon < 0$. Thus, from the switching point, we can infer the CRRA interval of the subject and thus the mid-point.

Under EUT, subjects linearly weight probabilities as such that subjective and actual probabilities induced by the experimenter are equal. This assumption is challenged under RDU theory (Quiggin 1982). Under RDU, we suspect that subjects often ascribe subjective probability weights to true probabilities. We use the specification of Tversky and Kahneman (1991) to describe subjective probability weighting as follows:

$$w(p) = \frac{p^{\gamma}}{[p^{\gamma} + (1-p)^{\gamma}]^{1/\gamma}} \quad \forall \quad 0 < p < 1, \tag{4.3}$$

Here, γ is the probability weighting parameter and p the probability of the respective MPL decision situation as ascribed by the experimenter. However, the specification does not behave well at its endpoints and subjects' sensitivity at the endpoints can be overweighted or neglected (Tversky and Kahneman 1992, p. 303). The graph in Figure 4.31 visualises the intuition of the probability weighting function. When subjects under-weight small probabilities ($\gamma > 1$), the *subjective* probability is lower than the actual probability. When $\gamma < 1$ and subjects over-weight small and under-weight large probabilities, $w(p)$ takes on its typical inverse S-shape. When $\gamma = 1$, $w(p) = p$ and $RDU = EU$. We integrate the probability weighting function $w(p)$ in the expected utility function (Equation 4.2) and obtain the RDU function of a lottery i.

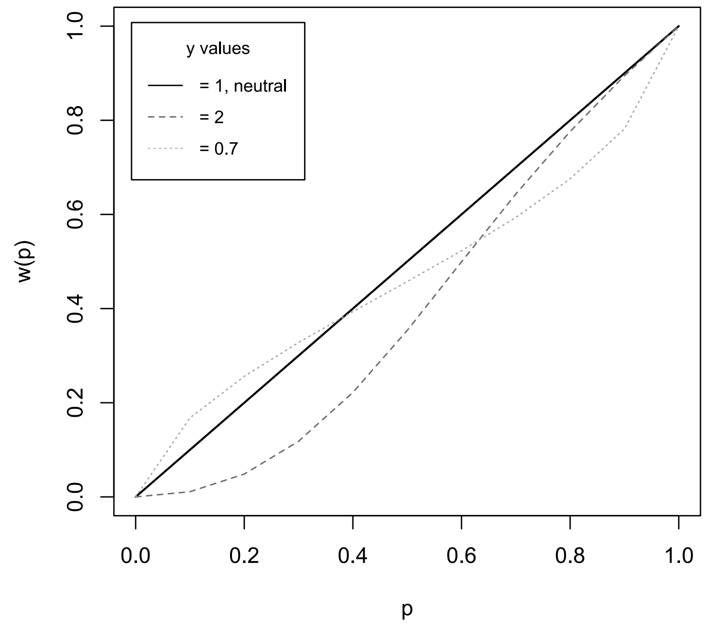

Fig. 4.31: Probability weighting function w(p) specification of Tversky and Kahneman (1991). Illustrative γ values are portrayed.

$$RDU_i = \sum_{k=1}^{K} (w_k \times U_k). \tag{4.4}$$

We stick to the CRRA specification of the utility function U_k in Equation 4.1. Taken together, subjects choose lottery B when $\Delta RDU = RDU(A) - RDU(B) + \epsilon < 0$.

Parameters are estimated using maximum likelihood estimation in line with Harrison (2008), Andersen et al. (2008) and Drichoutis and Lusk (2016). The index ΔEU and observed choices of the subjects are linked through a standard normal cumulative distribution function. We observe the choice y of subject i in decision situation j, where $y_{ij} = 1$ denotes the choice of lottery B and $y_{ij} = 0$ of lottery A. The log likelihood function thus depends on each subject's choice y_{ij} and estimates of r such that

$$\begin{aligned} \ln L(r, y); =& \\ & \sum_{i=1}^{N} \sum_{j=1}^{J} \left[\left(y_{ij} \times \ln \Phi(\Delta EU) \right) + \left((1 - y_{ij}) \times \ln \Phi(\Delta EU) \right) \right]. \end{aligned} \tag{4.5}$$

The same log likelihood function is applied to estimate the RDU model.

The structural model poses problems for various MLE algorithms in terms of convergence and sensitivity to starting values. We achieve an estimate of $r = 0.546$[12] for the EUT function, which is in line with studies on risk attitudes of European farmers (Iyer et al. 2020). We cannot compute reliable estimates for the RDU function. In the RDU model, γ can be estimated ($\gamma = 0.603$) but the related r value is out of bounds ($r = 7.523$).[13] Possibly, the estimation problems are an artefact of the MPL set-up, as the MPLs do not entail probabilities close to the endpoints (probabilities close to 0 and 1). Therefore, there are no data to fit these steep parts of the function and the information need to be drawn from the less informative, almost horizontal mid-part of the S-shaped curve (see Figure 4.31). These problems also arise when including observable characteristics (demographic covariates) to the EUT model that control for heterogeneity and should in principle improve the fit. Because of these estimation problems, we only use mid-point risk parameters to analyse our hypotheses in what follows.

We are not the first to report issues when estimating risk parameters with MLE (Just and Just 2016). In Zhou and Hey (2018), the model does not converge in 20 out of 96 cases for three distinct reasons: i) subjects have been either clearly risk-neutral or risk-loving, then the parameters are not unique, ii) subjects have not understood the tasks or have responded randomly or iii) estimations have hit the bound. We suspect that a combination of these three reasons causes the estimation and convergence issues in our study, too. Monotonicity has been violated eight times in the D&L lottery (8.2%) and five times in the H&L lottery (5.1%). There are 29 and 12 comprehension failures in the D&L and the H&L lottery respectively. Similarly, Drichoutis and Lusk (2016) find more monotonicity violations and comprehension failures in their own payoff-varying task compared to the standard H&L lottery. However, even when the observations with monotonicity violations and comprehension failures are excluded, the estimation issues remain.

Gao et al. (2022) suggest to use a Bayesian estimation approach to determine priors and MLE starting values because standard numerical methods often fail to converge. If the log likelihood function has a plateaued maximum, MLE methods may fail to converge. Also Rommel et al. (2022a) find that different conclusions can be drawn from different estimation strategies and that estimates are heterogeneous within and across samples. Nevertheless, they have successfully replicated the results from Bocquého et al. (2014) and conclude that CPT describes farmers' utility functions better than EUT. Within-sample heterogeneity (as for example in Rommel et al. (2022a)) indicates

[12] Same estimate with *bbmle* package (Bolker and R Development Core Team 2020) and *maxLik* package Henningsen and Toomet (2011); starting value of $r = 0.76$, standard error 0.034, $p < 0.001$, $logLik. = -740.94$ (df=1), AIC: 1483.889, BIC: 1495.664, 95% confidence interval: [0.48, 0.61]

[13] starting values: $r = 0.76$, $\gamma = 0.5$, all covariates = 0; computed with *maxLik* function (Henningsen and Toomet 2011)

that there is not one “winning” theory, but that some subjects are best modelled by one theory and others by the other, which in practice poses estimation problems (Harrison and Ross 2017).

4.4 Results

4.4.1 Sample Description and Treatment Effects

Out of 106 complete responses, eight observations are discarded. We discard one unreliable observation upon serious doubts about the truthful completion of the questions. Seven subjects have watched the informational video before the survey and are therefore excluded from the sample. Subjects in the control group that have watched the video are excluded to ensure a clean control. For subjects in the treatment group, the video might have been an activating reminder and these are therefore excluded. Further, 20% of the farmers indicate that they are using microbial applications and 42% mention that they have heard of the innovation before, mostly through specialised farmer magazines. Of these 42% of farmers that have heard of the innovation before, 14 are in the control group. We remove these subjects as a robustness check with a modified clean control group. These exclusion criteria and the robustness check have not been described in the pre-registration form, but are necessary for a clean control. The exclusions result in a sample size of N = 98 with 50 and 48 in the treatment and control group respectively. There is no evidence of structural misunderstandings or unperceptive watching behaviour: 97% of all questions are answered correctly.

According to Eurostat (2020), 58% of all Dutch farmers are 55 years old or older. In our sample, 40% of the farmers are 55 years old or older. The 1-sample proportions test reveals that the proportion of farmers aged 55 or older is significantly different from 0.58. Thus, our sample is younger than the general Dutch farming population. Compared to the overall farmer population, where 9% have received a full agricultural education and 69% have followed a basic agricultural education, our sample is on average more educated. With a total mean utilised agricultural area of 80 ha (σ = 67 ha), the farms in our sample are larger than the average Dutch arable farms with 60 ha according to 2018 FADN data, but there is also a large variation in the sample. At least one farmer from each province is included. The majority of farmers come from one of the arable-intensive provinces in the North of the Netherlands. The control group and treatment group have similar characteristics. Table 4.41 lists the overall farm and farmer characteristics and those per treatment group.

Our study falls into the time period of just after what we now know was the first wave of the COVID-19 pandemic in the Netherlands. None of the farmers in the sample have been infected with the coronavirus in the period between the start of the lockdown in the Netherlands (March 13, 2020) and the start of the distribution of the survey (July 17, 2020). However, in this time, there have been no reliable tests or self-tests available. The true number of infections in our sample might be higher. Although the majority of subjects do not know anybody that has been infected, half of the group indicates that they are at least “worried” about the virus.

Table 4.41: Descriptive and summary statistics of farm and farmer characteristics, including information on microbial applications: overall sample and different treatment groups.

Statistic	Overall sample					Treatment group					Control Group				
	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max	N	Mean	St. Dev.	Min	Max
male	89					44					45				
age[a]	98	1964	10.78	1940	1998	50	1965	11.07	1940	1998	48	1963	10.52	1940	1985
ha[b]	98	79.57	67.37	0	400	50	75.33	49.08	3	200	48	84.00	82.56	0	400
full-time[c]	98	0.77	0.43	0	1	50	0.74	0.44	0	1	48	0.79	0.41	0	1
organic	98	0.11	0.32	0	1	50	0.12	0.33	0	1	48	0.10	0.31	0	1
organisation	98	0.68	0.47	0	1	50	0.64	0.48	0	1	48	0.73	0.45	0	1
inhabitants[d]	98	50.36	43.27	6.86	232.92	50	49.14	43.15	6.86	232.92	48	51.63	43.81	10.94	232.92
microbial applications															
intention	98	56.02	31.47	0	100	50	68.22	28.72	1	100	48	43.31	29.34	0	100
using	98	0.21	0.41	0	1	50	0.26	0.44	0	1	48	0.17	0.38	0	1
familiar	77	0.51	0.50	0.00	1	37	0.68	0.47	0.00	1	40	0.35	0.48	0.00	1.00

Notes.

[a] year of birth [b] total: own plus leased land [c] 76% of the farmers operate their farm full-time and only 12% of the part-time farmers generate less than 40% of their income by farming. [d] in 1000

Main crops include ware (20%) and seed potatoes (17%), closely followed by wheat (13%) and starch potatoes (12%).

According to the RIVM data, on average, there are in total 1.71 cases per 1,000 inhabitants with a maximum number of 8.17 cases per 1,000 inhabitants in the time frame between the outbreak and the survey distribution. Table 4.42 shows a detailed overview. Subjective and objective measures of COVID-19 in the sample have limited variation.

Table 4.42: Descriptive statistics of COVID-19 proxies in the sample.

Statistic	N	Mean	St. Dev.	Min	Max
worried about corona[a]	96	3.05	1.02	1.00	5.00
infection in close circle[b]	98	0.32	0.47	0	1
total cases	98	7.44	6.14	1	32
per 1000 inhabitants					
new cases	98	0.18	0.15	0.04	0.94
hospitalised	98	0.09	0.11	0.02	0.58
deaths	98	0.05	0.04	0.00	0.18

Notes.

[a] Worry measured on five-point Likert scale, where a three is considered a neutral response, higher values indicate worry, lower values reflect unconcern. [b] 0 if no friend or family has been infected, 1 otherwise

Average MPL earnings are €22.59 with a maximum of €38.50 and a minimum of €1. Eight subjects have not provided their contact details and have not received their earnings. Eleven subjects have provided their contact details, but have indicated that they do not want to receive the payments. All other subjects have been payed out according to their choice. Regarding the randomised order of the MPLs and decision situations within each lottery, we find no order effect, which means that the data can be pooled.[14] Further, we find no association between the video treatment and switching points.

Risk attitudes are determined by average switching points in the MPLs and the associated midpoint parameters. The subjects switch on average in the 5th row ($\sigma = 3.4$) of the D&L lottery and in the 6th row ($\sigma = 2.9$) of the H&L lottery. Behaviour deviates from risk neutrality as depicted in Figure 4.41. Accordingly, the mean midpoint CRRA risk parameters are $r = 0.242$ and $\gamma = 0.995$

[14] There is no significant difference in the switching points of subjects that first conduct the D&L lottery (switching point H&L lottery M = 5.74, SD = 2.84; switching point D&L lottery M = 4.74, SD = 3.53) and the ones doing the H&L lottery first (switching point H&L lottery M = 5.63, SD = 2.96; switching point D&L lottery M = 4.96, SD = 3.35); H&L switching points: t(95) = 0.20, p = 0.8449, D&L switching points: t(95) = 0.31, p = 0.7542

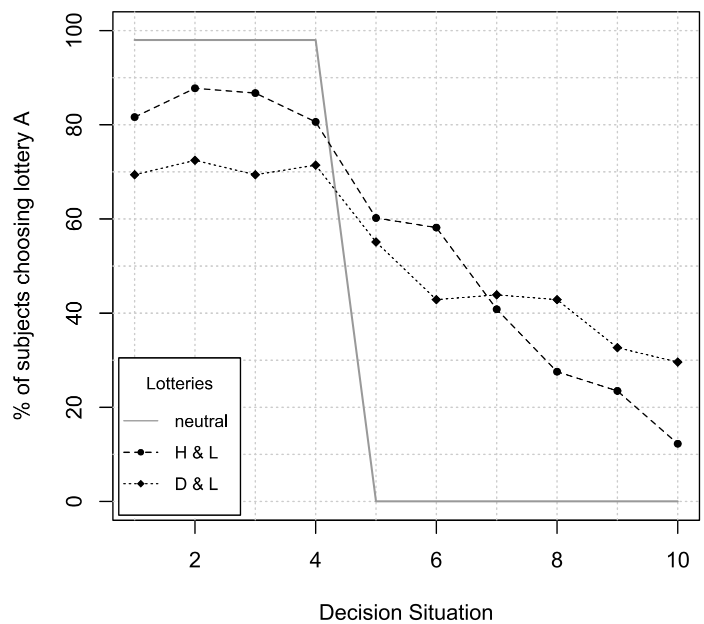

Fig. 4.41: Percentage of safe choices (choosing lottery A) per decision situation and lottery type.

(which is different in the structural model). This means the farmers in our sample are slightly risk-averse and over weight small probabilities.

On average, the intention to keep using/use microbial applications is 55 points. Trust in the safety of the product is 62.68 and in the efficacy is 55.7 as measured on a scale from 0 to 100.

4.4.2 Relationship between Risk, the Informational Video and the Use of Microbial Applications

In this section, we follow the structure of the pre-registration. We go step-by-step through each single hypothesis and its pre-registered and additional analyses.

Hypothesis 1: Farmers are more inclined to adopt microbial applications after watching a video explaining microbes in arable farming.

Our results suggest a positive effect of the video on microbial application adoption intentions. The mean intention to adopt microbial applications is significantly ($p < 0.001$) higher in the treatment group ($\mu = 68, \sigma = 28.72$) than in the control group ($\mu = 43.31, \sigma = 29.34$). As visualised in Figure 4.42, the variation of adoption intention is lower in the treatment group. The findings hold for current non-users and users of microbial applications. The findings also hold and are even more pronounced after removing the subjects from the control group who had some sort of prior knowledge. In the modified control group, the intention to adopt microbial applications is even lower ($\mu = 33.92$). The farmers that were exposed to information on microbial applications, but did not watch the video, increased the mean adoption intention of the sample by almost 10 points. This shows that prior information in general increase the adoption intention, but that the informational video is more effective.

The intention to use microbial applications is significantly and positively correlated with the farmer's trust in the efficacy ($cor = 0.86, p < 0.001$) and safety ($cor = 0.74, p < 0.001$) of the innovation. Trust in efficacy and safety is significantly larger in the treatment group than in the control group (efficacy: treatment group $\mu = 60.22, \sigma = 26.69$; control group $\mu = 45.56, \sigma = 26.16$; $p < 0.01$; safety: treatment group $\mu = 71.52, \sigma = 24.60$; control group $\mu = 52.4, \sigma = 30.42$; $p < 0.001$). The relationship between willingness to adopt microbial applications and trust in safety and efficacy is visualised in Figure 4.44. Thus, farmers who have watched the informational video are more willing to use microbial applications than those who have not.

An additional power analysis for the t-test on the stimulating effect of the informational video has been conducted ex-post, even though unconventional. We use the above means of the different control groups and the overall standard deviation to compute Cohen's d ($d = 0.79$). Results reveal that the two-sided t-test exhibits a power of 0.98.

Hypothesis 2: Farmers that are more affected by SARS-CoV-2 (coronavirus) are more risk-averse than farmers that are less affected.

We investigate the correlation between r midpoint estimates and γ estimates with the number of cases, hospitalisations and deceased, and the level of worry. None of the COVID-19 proxies, nor the subjective assessment variables, are significantly associated with the farmers' risk attitudes (see parts of the results in Table 4.43). Also, the two-sample t-test with farmers who know someone who has been infected and risk attitudes is not statistically significant ($p > 0.1$). For the lack of evidence of a short-term increase of risk aversion as a response to the COVID-19 pandemic, we refute the hypothesis. The results suggest no impact of the COVID-19 pandemic on risk attitudes of farmers in the short term.

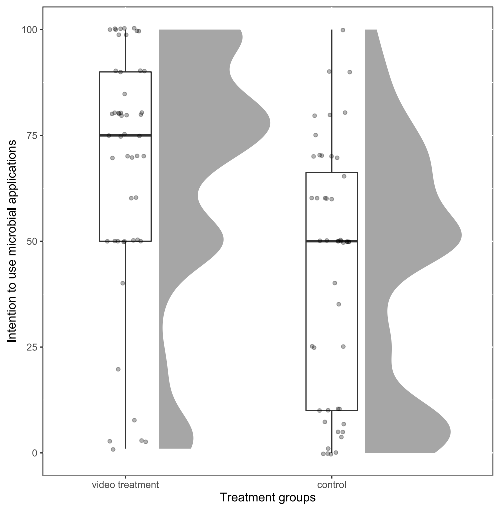

Fig. 4.42: Box- and density plot comparing the intention to adopt microbial applications between treatment groups, including raw data points. (H1)

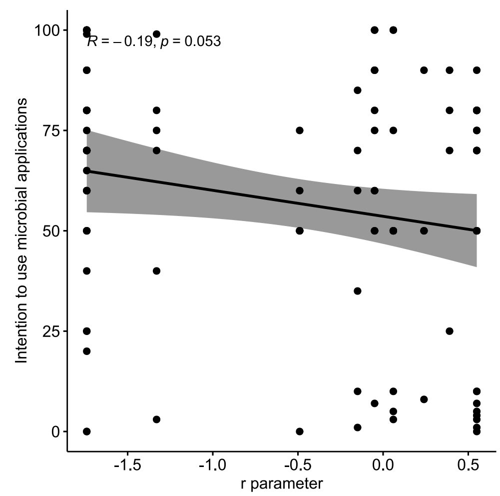

Fig. 4.43: Relationship between risk attitude and intention to use microbial applications. (H3)

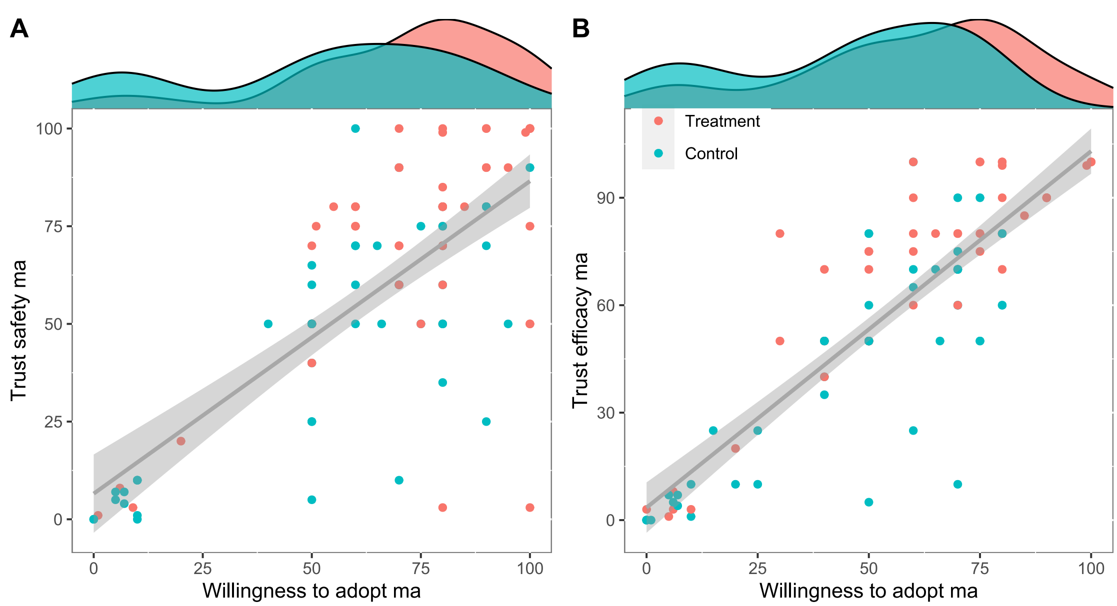

Fig. 4.44: Scatterplots visualising relationship between willingness to adopt microbial applications and trust in their safety (A.) and efficacy (B.). Density plots visualise distribution of trust in safety and efficacy respectively. Colours indicate different treatment groups. (related to H1)

Hypothesis 3: Farmers that are more risk-averse are less willing to adopt microbial applications on their farm.

The correlation analysis reveals that there is a statistically significant ($p < 0.1$), weakly negative correlation between risk attitudes and willingness to adopt microbial applications. In Figure 4.43 the relationship between the two is visualised and Table 4.43 summarises the findings. The results suggest that a higher risk aversion is weakly associated with a lower willingness to adopt microbial applications.

Table 4.43: Correlation matrix of risk attitude and COVID-19 (H2) and willingness to adopt microbial applications (H3) and of COVID-19 and willingness to adopt (H4).

	COVID-19				Willingness to	
	Cases[a]		Worried		adopt ma	
	cor	*p*	*cor*	*p*	*cor*	*p*
r	-0.021	0.83	0.042	0.68	-0.19	0.06
γ	0.047	0.64	0.060	0.56	0.001	0.99
Willingness to adopt ma	-0.135	0.18	-0.059	0.56	-	-

Notes. [a] per 1000 inhabitants in the same municipality

Hypothesis 4: COVID-19 is a predictor of the intention to use microbial applications on the farm.

The associations between the number of COVID-19 cases in a municipality and worry about COVID-19 with the intention to use microbial applications are not statistically significant (see Table 4.43). Thus, neither is the subjective assessment of COVID-19 found to be associated with the adoption of microbial applications, nor are the objective COVID-19 proxies significantly correlated with the adoption intention. We refute the hypothesis that the degree of being affected by COVID-19 is a predictor of the intention to use microbial applications on the farm.

Instead, the results of the regression analysis in Table 4.44 suggest that risk attitudes and agricultural education affect the willingness to adopt microbial applications. The more risk-loving a farmer, the more likely that she uses microbial applications. This is in line with our findings for Hypothesis 3. Farmers that have followed a practical education as compared to a full agricultural education are less likely to adopt microbial applications.

Table 4.44: Regression results. Dependent variable: intention to adopt microbial applications.

	Dependent variable:	
	Intention to use microbial applications	
	cor	*p*
r	−8.39	0.07
γ	−6.68	0.29
New cases per 1000 inhabitants	−47.02	0.42
Hospitalisation per 1000 inhabitants	−7.27	0.89
Deceased per 1000 inhabitants	14.70	0.91
Cumulative cases per 1000 inhabitants	3.73	0.45
Corona infected close	−2.04	0.82
Corona worried	1.44	0.74
Age	0.27	0.55
Male	−12.35	0.52
Education: Secondary I	38.69	0.32
Education: University	52.56	0.15
Education: Secondary II	52.80	0.16
Education: none	70.75	0.09
Education agri.: Practical	−5.06	0.65
Education agri.: Basic	−28.77	0.08
Education agri.: Other	−31.35	0.04
Successor maybe	−2.26	0.84
Successor yes	−0.66	0.96
Organic yes	2.09	0.87
Farmer organisation yes	4.99	0.59
UAA (in ha)	0.02	0.69
Fulltime	−7.89	0.39
Constant	−498.55	0.57
Observations	91	
R^2 (Adjusted)	0.28	(0.03)
Residual Std. Error	31.42	(df = 67)
F Statistic	1.11	(df = 23; 67)

4.5 Discussion

We assess the effect of an informational video on adoption intentions. We find that the informational video increases the farmers' willingness to adopt microbial applications. In this discussion, we focus on the treatment effect and the adoption of microbial applications. We also discuss the potential influence of risk attitudes and COVID-19 on adoption.

The informational video can be compared to nudges and other forms of interventions. With nudges, so-called choice architects or nudgers, aim to gently push people's decisions in a direction that is not exclusively to the benefit of the nudger by exploiting people's cognitive biases (Congiu and Moscati 2022). Our informational video does not exploit such cognitive biases, but only communicates information. However, the distinction between information, nudges, boosts and even marketing is blurry. For instance, most nudges depend on information (Ölander and Thøgersen 2014) and marketing often makes use of nudging tools (Congiu and Moscati 2022). Also boosts, which enhance the cognitive capacities of people by teaching them more effective decision principles, are based on information (Harrison and Ross 2018). When designing an intervention to stimulate the adoption of sustainable innovations, the entire behavioural intervention tool-kit and the combinations within it should be considered.

For instance, Ouvrard et al. (2020) find that a combination of a subsidy and an informational nudge are more effective than a subsidy alone. They conclude that the dissemination of information on the benefits of a technology increases its adoption, which is in their case a smart water meter. The results of our clean control experiment suggest that informational videos are effective. Videos seem to be particularly useful if one wants to convey a complex message or explain a complex technology. However, further research is needed to compare the effectiveness of information provision to nudges, such as social comparison nudges. Social comparison nudges are the most used nudges in the agricultural context: Treated farmers receive information on how many of their peers have adopted the innovation or practice in question. Results in previous studies on the effectiveness of such social comparison nudges are inconclusive. Kuhfuss et al. (2022) and Massfeller et al. (2022) both find no effect of social comparison nudges.

We recommend to consider the use of informational videos in campaigns on the adoption of sustainable farm innovations, eventually in combination with nudging tools. Informational videos can be a low-cost addition used in extension service. To date, the effectiveness of ICT-based tools, such as videos, has been proven in developing countries (David et al. 2011; Spielman et al. 2021; Vandevelde et al. 2021). These tools are able to raise the impact of extension services (Spielman et al. 2021) and increase the knowledge of farmers (David et al. 2011). A balanced expert panel should validate *ex ante* the information provided in the video. The receiver of the nudge, in our case farmers, should regard the issuer of the video, in our case a university, as an impartial, trusted source (Reddy et al. 2020).

The results suggest that the farmers in our sample are risk-averse, which is in line with other studies (Menapace et al. 2013; Iyer et al. 2020, for example). These risk-averse farmers are reluctant to adopt microbial applications. We support previous findings that suggest a hindering impact of risk aversion on adoption of innovations (Isik and Khanna 2003). Yet, risk attitudes elicited in lotteries do not always correlate with real world risk-taking behaviour (Rommel et al. 2019). So, considering that the risk attitude data are noisy, further research is needed to confirm that risk-averse farmers are more reluctant to adopt innovations. For example, noise can be reduced when the MPL order is not randomised or subjects indicate in which row they would like to switch. Other explanations than risk are also possible. Bougherara et al. (2017) find that farmers are risk-, ambiguity- and loss-averse. Ambiguity of microbial applications could have been reduced by the informational video, which in turn increases the farmers' intention to use microbial applications. Similarly, the informational video might have allowed farmers to better evaluate the risk associated with microbial applications which makes adoption more likely (Sagemüller and Mußhoff 2020).

The main limitations of this study are directly related to our cross-sectional data. Since we investigate *hypothetical* behaviour at one point in time, first, we cannot reliably state whether the adoption decision relates to real life settings, and, second, whether the treatment effect lasts over time. In *ex ante* analyses of innovations, hypothetical bias problems cannot be easily circumvented. Further, to investigate the long-term effect of the COVID-19 pandemic on risk and innovation adoption, panel data would be needed. The timing of the survey, just after the first wave, has been, in retrospect, not ideal. There is too little variation in the COVID-19-related data. Additionally, our sample is significantly younger than the overall Dutch farming population which might have influenced our findings. We also acknowledge that we do not correct for multiple hypothesis testing even though we test multiple hypotheses. In future studies, a Bonferroni adjustment should be considered (Noble 2009).

4.6 Conclusion

This study investigates the triangular relationship between the stimulating impact of an informational video and farmers' risk attitude on the intention to adopt microbial applications. In addition, we investigate the relationship between innovation adoption, COVID-19 proxies and risk attitude. Our analysis leads to three main findings. First, the video has a significant effect on the farmers' intention to use microbial applications in primary production, independent of the risk attitude of the farmers. Informational videos can be an effective, low-cost tool to stimulate the adoption of innovations such as microbial applications. Extension services can use videos to explain complex practices and innovations. National policy makers can use videos to explain the goals of the European Farm-to-Fork strategy (EC 2020) and how to reach them. Second, our results suggest that the intention to use microbial applications is influenced by the subject's risk attitude. Third, we do not find evidence that risk attitudes have changed in the short term after the first wave of the COVID-19 pandemic in the Netherlands. However, this is not a causal relationship, just an association, and due to various limitations of this study, this last conclusion is just an indication and further research is needed to test the reliability of this finding. Further, we conclude that especially well-educated and risk-loving farmers should be the first to approach when bringing microbial applications to the market.

We have several suggestions for future research. First, panel data and a replication of the study are required to measure the difference of risk attitudes during and after the pandemic. We recommend the combined use of the D&L and the H&L lottery. Second, while our study provides important insights into a specific area of research in innovation adoption, follow-up studies should investigate the effectiveness of informational videos beyond increasing the adoption intention of farmers and initiate actual behaviour and innovation adoption *ex post*. Third, the long-term robustness of the video should be tested. The effectiveness and persistent effect of the informational video should be compared with other types of incentives and combinations of nudges.

4.7 Appendix

Survey Design

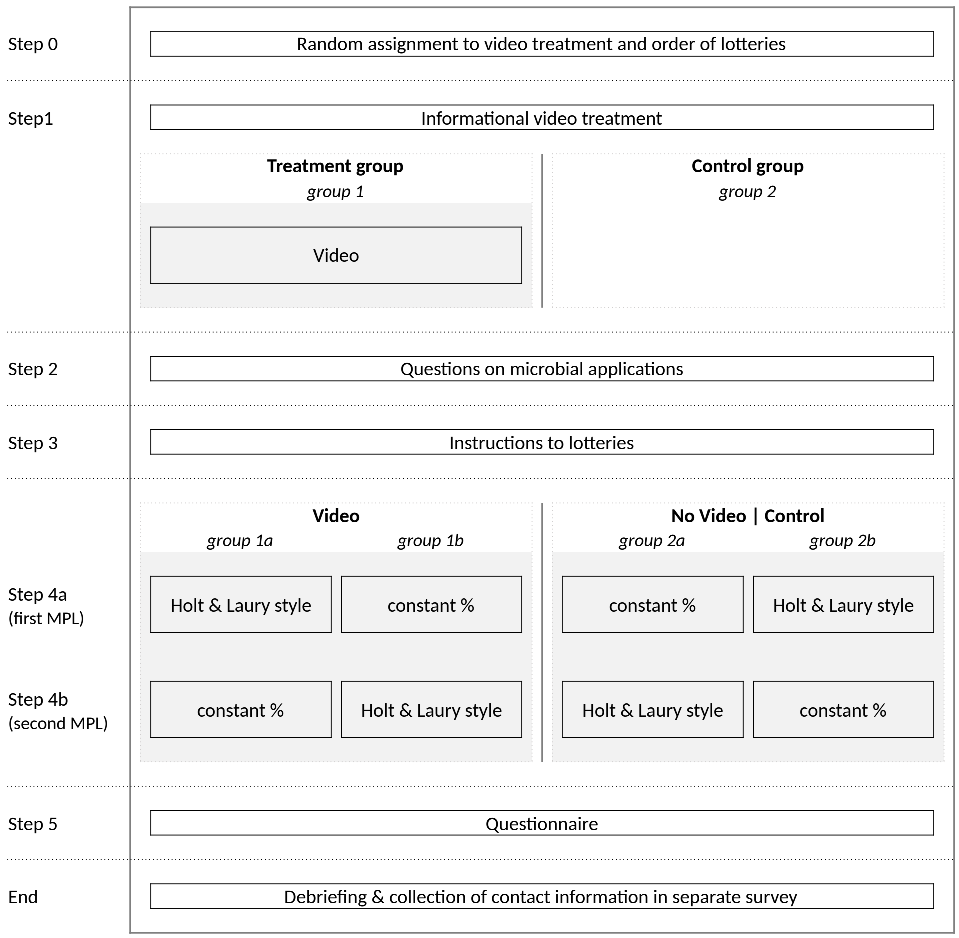

Fig. 4.71: Schematic representation of survey and experimental design with sequence of events.

Opportunity cost calculation

According to the European Farm Accountancy Network (FADN), the arable farm net income in the Netherlands in 2018 is €86,695. The farm net income is defined as the ”remuneration to fixed factors of production of the farm (work, land and capital) and remuneration to the entrepreneurs risks (loss/profit) in the accounting year”. When we divide this yearly income by $52 \times 5 \times 8$, even though we are aware that farming is not a classic 40 hour/week job, we get an hourly wage of €41.66.

At the same time, the family farm income is €73,002, which is defined as the income expressed per family labour unit. It “takes into account differences in the family labour force to be remunerated per holding. It is calculated only for the farms with family labour”. Using the family farm income as the basis, we obtain an hourly wage of €35.10.

Family farm income is the better estimate. Since it accounts for family labour, it provides a good proxy for the income per person. The income more than doubled between 2017 and 2018. The average over the last four years (2015–2018) is €29.64 (farm net hourly income) and €19.96 (family farm income, hourly). Both 2019 and 2020 are rather bad years for arable farmers in the Netherlands due to the drought and heat, as well as the corona pandemic (see e.g. “potato mountain” https://www.aardappelberg.nl/). Thus, we use €20 as a benchmark for the one-hour opportunity cost of a farmer. There are no data on the regional differences, but Dutch arable farms are rather homogeneous and no meaningful differences are to be expected.

Chapter 5

This Chapter is based on the paper

Tensi, A.F., Ang, F. & van der Fels-Klerx, H. J. (2022). Microbial Applications and Agricultural Sustainability: A Simulation Analysis of Dutch Potato Farms. *Submitted to a Journal*.

Microbial Applications and Agricultural Sustainability: A Simulation Analysis of Dutch Potato Farms

Abstract Fertilisers and plant protection products are essential for the economic viability of arable agriculture, but their overuse leads to environmental problems. Microbial applications have been proposed as a solution to reduce these environmental problems in arable farming. Experimental results suggest that microbial applications can increase yields and reduce abiotic stresses with fewer fertilisers and plant protection products. However, the overall effects of microbial applications on farm economics, the environment and social dimensions have not been quantified yet. In this study, we assess the capacity of microbial applications to enhance the sustainability, including environmental, economic and social dimensions, of Dutch potato production. We model a baseline scenario and a microbial application scenario with Monte Carlo simulation, and compare the scenarios using a composite sustainability index. The microbial application scenario is based on data from a Delphi expert elicitation. The results show that microbial applications are sustainable, but cannot yet enhance the sustainability of Dutch potato production. Microbial applications' three main disadvantages are their costs, which exceed the benefits, their effect uncertainty, and their inability to prevent potato diseases. The main advantages are their positive effect on the environment by reducing CO_2 emissions and active substances, and the potential yield increase. Technological advancements are required to further reduce the costs per unit of production and increase environmental sustainability. In this way, microbial applications can be part of the solution to enable the sustainable transformation of agri-food systems. The results of this study contribute to an understanding of the implicit uncertainty of microbial application effects. Although effect uncertainty is mentioned in other studies, we explicitly quantify it as a core element in our model.

Keywords: Microbial Applications, Simulation Modelling, Delphi, Expert Elicitation, Dutch Potato Production

5.1 Introduction

Fertilisers and plant protection products (PPP) are essential for the economic viability of arable agriculture, but their overuse leads to environmental problems (Sud 2020; Sidhoum et al. 2020; Skevas et al. 2014). In light of this, the European Commission has introduced the 'Farm to Fork' strategy: Farmers need to use 50% fewer PPP and 20% fewer fertilisers by 2030 compared to the baseline average of 2015 – 2017. In Dutch arable agriculture, the Farm to Fork reduction goals for fertilisers have almost been met in 2020,[1] but continued reduction efforts are needed for PPP. The use of active substances in 2020 has been twice as high as the 2030 reduction goal.

Potatoes are important for world-wide food security, but their input-intensive production has a considerable environmental footprint (Koch et al. 2020). For example, in the Netherlands potatoes are produced on 31% of arable farm land (in total 166, 000 hectares for starch, seed and consumption potatoes) from which 1.3 million tonnes of consumption potatoes have been exported in 2020 (Berkhout et al. 2022). In Dutch seed potato production, 37.9 kg ha^{-1} active substances are used. This is seven times more than what is used in sugar beet production (5 kg ha^{-1}), another input intensive crop in the Netherlands (Smit 2022). Farmers apply active substances in PPP to mitigate production risks, such as yield and quality reducing nematodes (Herrera et al. 2022; Orlando et al. 2020), and *Phytophthora infestans*. *Phytophthora* causes potato late blight, the most important disease in potatoes (Schepers et al. 2018). To reduce the use of active substances, farmers need reliable alternatives. Switching to alternative products will be less of a choice than a necessity, as some harmful active substances are already or will be banned in the near future (Goffart et al. 2022). To date, possible alternatives like microbial applications are understudied (Aloo et al. 2020).

Microbial applications have recently been proposed as an innovative solution that simultaneously reduces the need for PPP and fertilisation, increases yields and alleviates drought and other abiotic stresses (Belimov et al. 2015; de Souza et al. 2015; Gong et al. 2020; Grossi et al. 2020; Lutfullin et al. 2022). A microbial application is a consortium of various microorganisms (Tshikantwa et al. 2018). Beneficial rhizobacteria, microorganisms living in the root-soil interface, can improve the productivity and quality of crops, suppress plant diseases and control pathogens (Gouda et al. 2018).

To date, data on the performance of microbial applications are scarce and preliminary (Kołodziejczyk 2014). First experimental results suggest the potential of microbial applications (Elnahal et al. 2022), but their costs, effectiveness in reducing PPP and fertiliser use, and in increasing crop yield have not been reliably quantified (Mitter et al. 2019; Shameer and Prasad 2018).

[1] own calculations (see 5.6), based on Agrimatie data

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First calculations show that production costs of microbial applications are not yet competitive with available chemicals (Lobo et al. 2019). Consequently, the number of microbial products on the market is limited (Russo et al. 2012), as is the number of farmers using microbial applications. Overall environmental and economic effects of microbial application use are unclear and social aspects of microbial applications have not been investigated yet. Therefore, the overall impact of microbial applications on the sustainability of agricultural production is unclear.

In this study, we aim to assess the capacity of microbial applications to enhance the sustainability, including environmental, economic and social dimensions, of primary food production systems. We focus on the Dutch potato production system and answer the research question 'How do microbial applications influence the sustainability of Dutch potato production?' We model a baseline potato production system (hereafter called baseline scenario) and a potato production system that incorporates microbial applications (hereafter called microbial application scenario) with Monte Carlo (MC) simulation, and compare the scenarios with a composite sustainability index. The microbial application scenario is based on data from a Delphi expert elicitation. We provide insights into advantages and disadvantages of using microbial applications.

5.2 Materials and Methods

5.2.1 Model Structure

We employ a MC simulation model to simulate the environmental, economic and social outcomes of a Dutch potato production system with and without microbial applications. In the *baseline scenario*, the parameters and distributions are based on historic production data and literature. The *microbial application scenario* is the baseline scenario multiplied by the *microbial change model*. In the microbial change model the effects of microbial applications on the amount of production inputs and outputs is quantified. Parameters of the microbial change model are drawn from a Delphi expert elicitation study. The overall model is a static stochastic partial budget model. We investigate the changes in environmental, economic and social indicators when microbial applications are used in potato production, as compared to the baseline. The model outputs are aggregated in a composite sustainability index. See Figure 5.21 for a visual summary of the model structure.

The system boundary of the MC simulation model is the farm gate. The unit of analysis is one hectare of conventional potato production in the Netherlands in the time frame of one growing season. We distinguish between seed, starch and consumption potato production. Results are provided per production scenario, aggregating the three potato crops.

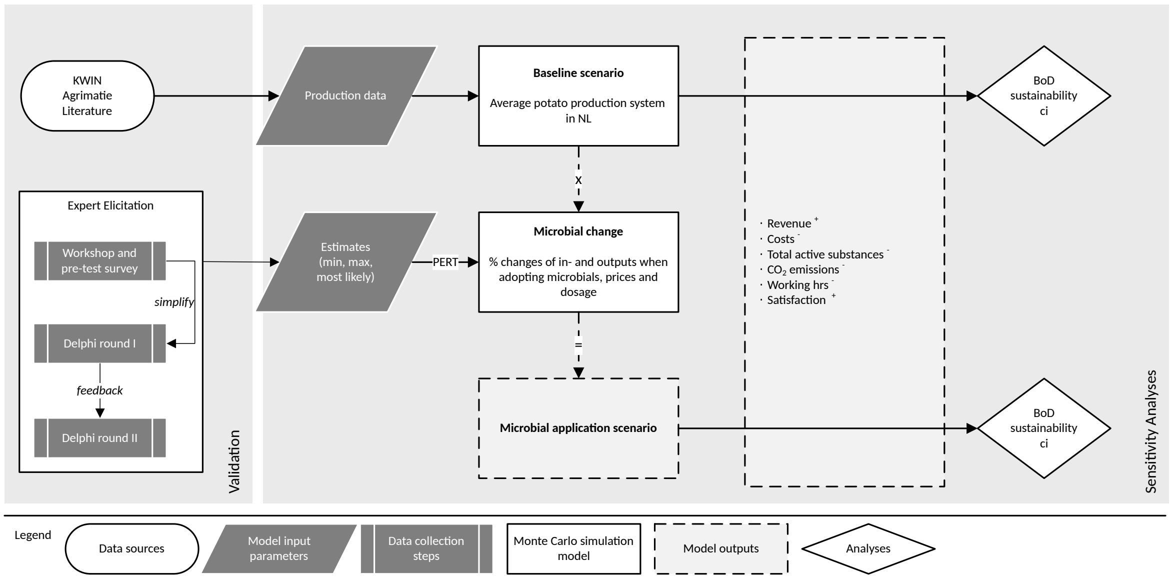

Fig. 5.21: Visualisation of the structure of the model, its input data, outputs and analyses.

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The baseline scenario reflects the average potato production system in the Netherlands in 2010 to 2018. We simulate N=500 hectares of consumption potatoes and N=250 hectares each of seed and starch potatoes to reflect the true shares of utilised agricultural area of each potato crop. We assume average Dutch growing conditions in terms of weather, soil and location for each potato crop and average management in terms of production inputs and outputs. We assume that microbial applications are allowed by legislation and that farmers apply microbials and other production inputs at the ideal dosage. We assume all other inputs, such as seedlings, energy, and working hours for the harvest, to be fixed. There are six key model output variables (elaborated in 5.2.3): Revenue (yield × selling price), costs for fertilisers and PPP, total active substances (sum of active substances in insecticides, fungicides and herbicides), CO_2 emissions of fertiliser production and application, working hours and satisfaction.

5.2.2 Input Data

5.2.2.1 Baseline data

The baseline model input parameters and their distributions are summarised in Table 5.21 below. The model variables are grouped into economic and environmental in- and output factors and social factors. Each variable is described and the parameter sources are provided. To introduce variability in production, we impose stochasticity on all variables, except for production input prices. Stochasticity is introduced because there are large differences in yield between fields and farms (Den et al. 2022). Prices for fertilisers and PPP are fixed because of low price variability in the considered time frame.

5.2.2.2 Expert Elicitation

Microbial applications are not widely available on the market, but mostly in the research and development phase. Therefore, only a few reliable data sources are available on their potential effectivity. To address this information and data gap, we have elicited experts' data on microbial applications. The expert elicitation has the form of a Delphi study. The Delphi method is based on seminal work by Dalkey and Helmer (1963). A Delphi study is a structured, iterative consultation process with feedback rounds in which results are given back to the panel (Linstone and Turoff 2011). Experts are allowed and encouraged to amend their judgements after seeing the group results. Delphi studies happen either in a group setting or anonymously. The latter is a way to reduce the bias that dominant individuals can introduce to a group (Jones et al. 2017).

The goal of the Delphi expert elicitation is to gain parameters to quantify the microbial change model. In the beginning of the process, we specify the baseline and microbial application scenarios and our assumptions. The experts provide estimates on the minimum, maximum and most likely effect of microbial applications. Effects are expressed in percentage change of yield, fertiliser and PPP use and prevalence of diseases. Baseline satisfaction, a score of five points on a scale from one (dissatisfied) to ten (very satisfied), is given and experts estimate the score for adopters. Further, the experts provide absolute three point estimates on the current and future prices and dosage of microbial applications. All three point estimates are used as inputs for PERT distributions in the microbial change model. PERT distributions are frequently used when relying on subjective expert estimates as the three point parameters are intuitive for experts (Werner et al. 2017). We also ask the experts how they would weigh each of the three sustainability dimensions. When the three sustainability pillars are combined in one index, these pillars need to be weighted and trad-offs are created. We ask the experts 'Which weight would you give to each sustainability pillar, adding to 100% and considering the Dutch arable farming sector?'

The expert elicitation consists of three rounds, namely a two-hour workshop with a pre-test of the survey in June 2022 and two Delphi iterations. During the workshop, we present the research questions and background of our study, why we involve experts, and how we use the experts' estimates. After this introductory presentation, the experts fill in the pre-test survey online which we discuss afterwards. The survey questions are based on Foolen-Torgerson (2022, Chapter 3).

Table 5.21: Baseline model parameters, distributions and parameter sources for each potato crop.

Variable	Default			Description	Source
	Starch	Seed	Cons	*Distribution*	
A. Farm Inputs, amounts and prices					
PPP, amount in kg ha^{-1}				With a minimum threshold of 3 kg ha^{-1}, most important PPP are selected per crop. We compute average for different production regions and soil types. PPP use simulated with a truncated normal distribution. Lower bound is = 0.	KWIN-AGV (2018)
Insecticides	$\mu = 10.0$	$\mu = 0.00$	$\mu = 2.50$		
Fungicides	$\mu = 4.04$	$\mu = 3.31$	$\mu = 4.33$		
Herbicides	$\mu = 4.50$	$\mu = 3.80$	$\mu = 3.06$		
				$\xi(\mu, \sigma = 2, a = 0, b = \infty)$	
PPP, costs in €kg^{-1}				With a minimum threshold of 3 kg ha^{-1}, we selected the most important PPP for each potato crop. We use the average price of these inputs in the simulation model.	KWIN-AGV (2018)
Insecticides	14	-	3.5		
Fungicides	32.33	36.5	34.1		
Herbicides	16.25	13	24.91	*Fixed*	
Fertilisers, amount in kg ha^{-1}				For starch, there is only one production area provided in KWIN. Therefore, we use a normal distribution N with standard deviation = 1. For the other potato products, we use the minimum and maximum values from KWIN as the bounds in a continuous uniform distribution U.	KWIN-AGV (2018)
N	$\mu = 230$	$a = 0$, $b = 140$	$a = 188$, $b = 250$		
P	$\mu = 60$	$a = 20$, $b = 185$	$a = 50$, $b = 60$		
K	$\mu = 110$	$a = 0$, $b = 320$	$a = 140$, $b = 210$	$N(\mu, \sigma = 1)$ *or* $U_{[a,b]}$	
Fertilisers, costs in € 100 kg^{-1}				These are the average prices for the different fertiliser products. The prices are identical for the different potato crops.	KWIN-AGV (2018)
N		114			
P		78			
K		50		*Fixed*	

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Table 5.21 continued.

Variable	Default			Description	Source
	Starch	Seed	Cons	*Distribution*	
B. Farm Outputs, amounts and prices					
Yield in to ha^{-1}	$\alpha = 64.79$, $\beta = 1.62$	$\alpha = 352.75$, $\beta = 9.89$	$\alpha = 186.17$, $\beta = 3.83$	We analysed the yield data from 2010 to 2020 and fitted a gamma distribution with by maximum likelihood estimation. The resulting distribution parameters (shape α, rate β) have been used to simulate yield. $Gamma(\alpha, \beta)$	CBS (2022)
Price in €100 kg^{-1}	$\mu = 7.71$, $\sigma = 1.3$, $a = 5.18$	$\mu = 28.89$, $\sigma = 3.37$, $a = 24.68$	$\mu = 14.36$, $\sigma = 4.63$, $a = 7.55$	Average prices for potato products between 2010 and 2021. We computed the average and standard deviation of the price data. These are used together with the min bound a. $\xi(\mu, \sigma, a, b = \infty)$	Agrimatie (2022)
C. Environmental Inputs					
Active substances in kg ha^{-1}				Average active substances used from 2010-2020 *Triangular (a, b, c): $a \leq c \leq b$*	Agrimatie (2022)
Insecticides	$a = 0.02$, $c = 0.04$, $b = 0.06$	$a = 0.21$, $c = 0.25$, $b = 0.34$	$a = 0.05$, $c = 0.22$, $b = 1.78$		
Fungicides	$a = 9.27$, $c = 13.2$, $b = 16.11$	$a = 5.64$, $c = 7.33$, $b = 8.93$	$a = 5.43$, $c = 8.37$, $b = 9.93$		
Herbicides	$a = 1.13$, $c = 2.01$, $b = 3.44$	$a = 1.78$, $c = 2.49$, $b = 3.24$	$a = 2.64$, $c = 3.33$, $b = 3.85$		

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Table 5.21 continued.

Variable	Default			Description	Source
	Starch	Seed	Cons	*Distribution*	
D. Environmental Outputs					
CO_2 footprint inputs in kg CO_2 per tonnes of potato yield				Environmental 'cost' of potato production. Provided in Table 13 of the cited source. Normally distributed with $\sigma = 2$.	Goffart et al. (2022)
Fertiliser production	$\mu = 12$	$\mu = 40$	$\mu = 25$		
Fertiliser emission	$\mu = 32$	$\mu = 18$	$\mu = 25$		
Biocides	$\mu = 10$	$\mu = 16$	$\mu = 5$	$N(\mu, \sigma = 2)$	
Total environmental points per ha of potato crop				Total environmental impact of PPP, expressed in points as calculated by WEcR, for soil, ground and surface water per hectare of potato production. Not all PPP have the same environmental impact. This has been taken into account when calculating environmental burden.	Agrimatie (2022)
Soil	$a = 250$, $c = 714.55$, $b = 1120$	$a = 310$, $c = 529.09$, $b = 930$	$a = 240$, $c = 466.36$, $b = 690$		
Groundwater	$a = 570$, $c = 650.91$, $b = 730$	$a = 100$, $c = 167.27$, $b = 280$	$a = 250$, $c = 383.64$, $b = 790$		
Surfacewater	$a = 980$, $c = 1763$, $b = 3590$	$a = 1430$, $c = 1830$, $b = 3210$	$a = 1170$, $c = 1884$, $b = 2950$	*Triangular (a, b, c):* $a \leq c \leq b$	
E. Social					
Working hours per ha potato crop for each activity					KWIN-AGV (2018)
Tillage		$\mu = 6.1$		Identical for all potato crops. Provided in KWIN	
Fertilising		$\mu = 1.2$			
PPP		$\mu = 6.5$		$N(\mu, \sigma = 1)$	
Satisfaction		$\mu = 5$		$N(\mu, \sigma = 1)$	*This study*

The pre-test allows to clarify questions on the spot and simplify the survey later. For instance, in the pre-test survey, we ask experts to elicit the effects of microbial applications for seed, starch and consumption potatoes separately. It turns out that the expected effect is the same for different potato crops, and we ask for estimates of the average effect of all production systems together in subsequent rounds.

In the second round, the first Delphi iteration, we use the simplified survey and ask the experts to provide their estimates (again). The online survey is sent via e-mail on June 27, 2022 and a reminder is sent on July 6, 2022. Participation takes circa 30 minutes. In the last round, the second Delphi iteration, the responses of round two are summarised and returned to the panel for further reflection in the form of another online survey. The link is sent out via e-mail on August 9, 2022 and two reminders are sent two and three weeks later. We show summary statistics (mean, standard deviation, minimum and maximum) of each lower and upper bound and most likely estimate from the previous round. We ask the experts to take a look at the means and evaluate whether they seem reasonable. The remaining summary statistics provide an indication on the distribution of the estimates. We ask the experts whether they want to confirm the provided estimate means. They do not have to agree with the colleagues but are encouraged to see it as an incentive to rethink and review the estimate. If they can not agree, they are asked to provide new estimates. We also ask the experts to justify the satisfaction estimates they have provided. We ask 'what does farmer satisfaction entail and how can it change through microbial application use?' In both of the last two rounds, we encourage participation by all experts, even if they did not participate in the previous round. In the last round, participation time is reduced to 20 minutes. The expert elicitation surveys are provided in the Supplementary Material.

The simulated effect of microbial applications is based on the confirmation rate, the degree to which experts agree on the estimates of an effect. We define the confirmation rate as the percentage of experts agreeing on the mean estimate from the previous round. If the confirmation rate is less than 75%, this indicates that some of the experts have a strong opinion about the variable and cannot agree with the estimates of their peers (Diamond et al. 2014). Then, the final change rate is computed 50% on the second round and 50% on the third round. When the confirmation rate is 80%, the change rate is based 80% on the third round and 20% on the second round. If the confirmation rate is larger or equal to 90%, we only use the final round results. Such corrections are customary in expert elicitation analyses (Dalkey and Helmer 1963).

The majority of experts in our panel are researchers in academia and institutes, in addition to a few participants from industry. Their expertise spans diverse disciplines, from agronomy to microbiology. Their identity is known to the authors, and experts could choose to provide answers anonymously or with an identifier. All experts are directly involved in the European Horizon 2020 SIMBA project. Thus, the panel has heterogeneous backgrounds but is a coherent group. The entire panel consists of sixteen experts, who have all been invited to partake in the workshop to pretest the survey and to the two-iteration Delphi study. Twelve of the experts have pretested the questionnaire and five and ten answers have been recorded in the two Delphi iterations respectively.

5.2.2.3 Validation data

We discuss validation data together with our findings in the results section. We comment on similarities and differences, and discuss sources for the latter. We use three sources of data and information to validate our baseline and expert input data and results: i) unpublished data from a SIMBA farmer survey on potato and wheat farmers in the Netherlands (Slijper et al. 2022), ii) industry information and iii) literature. In the SIMBA farmer survey (Slijper et al. 2022), fifty-two non-adopters and thirty-three adopters provide data on their potato production in the Netherlands. The summary statistics of these data (Table 5.22) are discussed together with the microbial application scenario. Another valuable source for validation are industry data. One of the few providers of microbial applications in the Netherlands provides pricing and dosage information. These are discussed in conjunction with the microbial application model results and used as input for a sensitivity analysis.

For model validation purposes we explore the literature on *Web of Science* and *GoogleScholar*. We specifically search for greenhouse and/or field experiments conducted in Europe on potatoes with plant growth promoting rhizobacteria and microbial applications. We exclude reviews and the large number of studies conducted in Asian countries. These studies are not informative for the European context because climate and soils are not comparable. We limit our search to the time frame of beginning of 2010 to the beginning of 2022. Further details on the literature search, including the search term, are provided in 5.6.

5.2.3 Composite Sustainability Index

We aggregate a sustainability index for each of the two scenarios. An aggregated index provides a more concise overview when looking at multiple variables (Luzzati and Gucciardi 2015), allows direct comparison of multiple scenarios (Munda 2005) and quantifies trade-offs between sustainability pillars. Each of the three sustainability dimensions is represented by two single indicators, which are aggregated in the composite sustainability index. The economic dimension is represented

Table 5.22: Summary statistics of SIMBA farmer survey: Selected input and output data of non-adopters compared to adopters of microbial applications.

	Non-adopters (N = 91)			Adopters (N = 42)		
	N	Mean	St dev	N	Mean	St dev
Fertiliser use and costs						
N (kg ha^{-1})	65	150.72	173.74	35	151.51	187.88
P (kg ha^{-1})	62	12.88	23.31	35	15.61	20.06
K (kg ha^{-1})	62	52.01	53.84	33	67.62	66.02
Cost (€ha^{-1})	63	84.96	111.86	35	88.17	98.14
PPP use and costs						
Use (kg ha^{-1})	38	8.77	11.12	27	6.34	6.14
Cost (€ha^{-1})	38	408.27	518.11	27	295.22	285.92
Farm outputs (tonne ha^{-1})						
Seed potato yield	12	40.12	3.12	11	39.14	5.12
Ware potato yield	27	55.76	9.89	18	54.42	7.48

Notes. Unpublished data from Slijper et al. (2022).

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by the single indicators revenue and costs. The environmental dimension is represented by the single indicators active substances and CO_2 emissions. The social dimension is represented by the single indicators working hours and satisfaction. We select relevant indicators from Van Asselt et al. (2014) based on whether we expect the single indicators to change due to microbial applications, and based on data availability (Niemeijer 2002). We normalise the single indicators with the min-max method ($Y = \frac{x - x_{min}}{x_{range}}$). An overview of the single indicators and their normalisation sign is provided in Figure 5.21 (see the dashed box on the right-hand side of the figure).

Each normalised single indicator is first multiplied with an indicator specific weight w_p and then aggregated into a composite index ci. We use (and compare) two different weighting methods. First, we use the weights provided by the experts in the survey. We compute the average weight for each dimension, which could - in theory - exceed 100% in total. We assume that each single indicator contributes equally to its respective sustainability dimension. The composite expert index ci is computed as $ci = \sum_{i=1}^{I} \frac{w_p}{2} i_s$, where w_p is the average dimension specific weight provided by the experts.

Second, we use the Benefit-of-the-Doubt (BoD) approach (Cherchye et al. 2007). This approach is based on an input-oriented Data Envelopment Analysis (DEA) model. DEA is a linear program optimisation method. With the BoD approach, observation-specific weights are endogenously assigned such that the composite index yields the highest possible score and the objective function of each observation is maximised. For each observation f, we solve the following optimisation problem:

$$max \sum_{f=1}^{S} w_{fi} I_{fi} \tag{5.1}$$

$$s.t.: \quad \sum_{f=1}^{S} w_{fi} I_{fi} \leq 1 \qquad \forall f = 1, \ldots, N \tag{5.2}$$

We maximise each observation's composite sustainability index ci. The normalised score I_{fi} of the i^{th} single indicator of observation f is weighted with the endogenous weight w_{fi} (Gan et al. 2017; Van Puyenbroeck and Rogge 2017). The resulting ci cannot exceed one.

We pool the simulated data from both scenarios to compute the BoD ci of each observation. Thereby, we compare each observation with all observations in both scenarios. In addition, we have three robustness checks in place in which we pool the simulated data differently before computing the BoD. Each observation is compared to different peers then and because the BoD ci is a relative measure, individual final indices are affected. First, we pool all observations from the baseline and microbial application scenario and all sensitivity analyses and then compute the BoD ci. Second, we only pool the microbial application scenario and its sensitivity analyses and then compute the BoD ci. Third, we compute the indicator weights for each observation in the baseline scenario and use these weights to compute the sustainability indices for the microbial application scenario.

5.2.4 Sensitivity Analyses

With the sensitivity analyses, we investigate the consequences of a microbial application price and effectivity change. The sensitivity of prices for microbial applications is assessed by reducing the prices by 30% and by using estimated future prices. To assess the sensitivity of microbial application effectivity, we look at the effect of a 10%, 30% and 50% raise in yield increase, and fertiliser and PPP reduction potential. In a separate sensitivity analysis, we use the industry values for prices, dosage and effectivity. We also investigate the sensitivity of the baseline and microbial application scenarios to an increase in fertiliser and PPP prices. All sensitivity analyses are summarised in Table 5.23.

We assess the sensitivity of the production system to a change in these variables in two ways. First, we visually assess how the change affects the main output variable and the sustainability index. Second, we conduct two-sample t-tests on the sustainability indices from different scenarios

Table 5.23: Overview of sensitivity analyses: variable change and scenario.

Sensitivity analyses	Variable changes	Applied to scenario
Effectivity of microbial applications:		
Fertiliser reduction potential	−10%, −30%, −50%	ma
PPP reduction potential	−10%, −30%, −50%	ma
Yield increase	+10%, +30%, +50%	ma
Price changes:		
Conventional fertiliser	double, triple	baseline, ma
PPP	+10%	baseline, ma
Microbial applications	potential future prices, −30%	ma
Industry example	dosage $N(\mu = 35.8, \sigma = 1)$, price $U_{[8,10]}$; yield: consumption pot. $N(3.9, 2)$, seed pot. $N(7.5, 2)$	ma

Notes. ma = microbial change scenario

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to evaluate if a change in the models' parameters has an influence on the sustainability of the production system.

5.3 Results

5.3.1 Expert Elicitation

In the final expert elicitation round, three variables have a confirmation rate of 80%: microbial application dosage, and the reduction potential of herbicides and insecticides. Two variables have a confirmation rate of less than 75%: the reduction potential of fungicides and microbial application prices. All other variables have a confirmation rate of at least 90%. The parameters for the change model are computed accordingly.

The summary statistics of the consolidated expert elicitation results are provided in Table 5.31. The large standard deviations and confirmation rates for dosage, prices and fertiliser use verify the earlier noted uncertainty. We present the probability densities and the cumulative distribution functions (cdf) of the most important variables in Figures 5.31 and 5.32. According to industry data, the current advised dosage of microbial applications is between 8 and 10 kg ha^{-1}, and prices are around €33.80 kg^{-1}. Based on these industry figures, current dosage and market prices are overestimated by the experts: Estimated dosage is twice the industry dosage, and estimated prices are

Table 5.31: Summary statistics of consolidated expert estimates: dosage, current and future prices, effect of microbial applications on potato production in %, working hours, farmer satisfaction; mean sustainability dimension weights used in index construction.

Statistic	Mean	St. Dev.	Min	Max
Microbial application				
Dosage (in kg ha^{-1})	69.19	16.69	33.08	114.89
Price (in €/kg)	223.45	38.99	155.77	352.34
Future price (in €/kg)	172.26	22.67	133.42	246.86
Fertiliser usage (expected change in%)				
N	−20.30	4.80	−35.53	−11.17
P	−12.35	4.07	−26.08	−5.11
K	−25.73	6.64	−43.42	−12.52
PPP usage (expected change in%)				
Fungicides	−7.36	2.45	−17.58	−3.48
Insecticides	−5.74	1.35	−13.50	−4.60
Herbicides	−4.34	3.03	−14.85	0.08
Irrigation (expected change in%)	0.77	0.88	−1.46	2.83
Effect on ecosystem health (in%)	6.92	2.02	2.21	12.34
Yield change (in%)	3.73	3.40	−3.62	12.12
Potato price change (in%)	5.78	1.93	1.72	11.01
Prevalence of diseases (in%)	−0.22	2.47	−6.94	5.72
Working hours (expected change in%)				
Application of PPP	−6.85	1.48	−10.45	−3.95
Fertilisation	−6.88	1.43	−11.16	−3.88
Tilling	−5.51	1.11	−8.43	−3.20
Application of microbes (in hrs)	11.18	2.60	5.28	18.05
Farmer Satisfaction (on a scale 1-10)	6.28	2.92	0.13	13.74
Sustainability dimension weights				
Economic	0.35			
Social	0.27			
Environmental	0.37			

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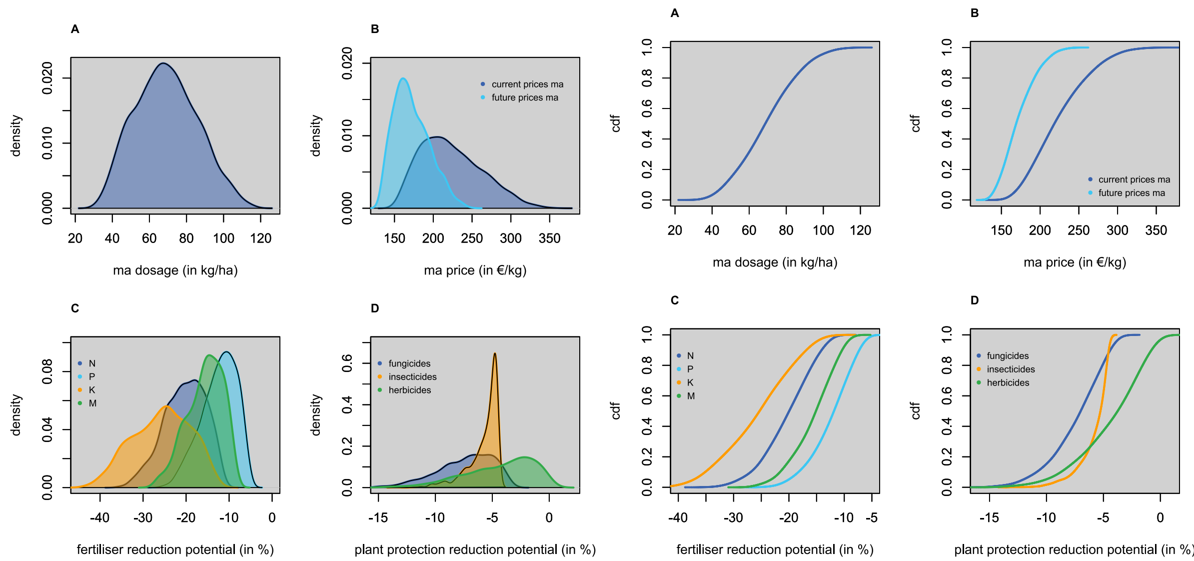


(a) Densities

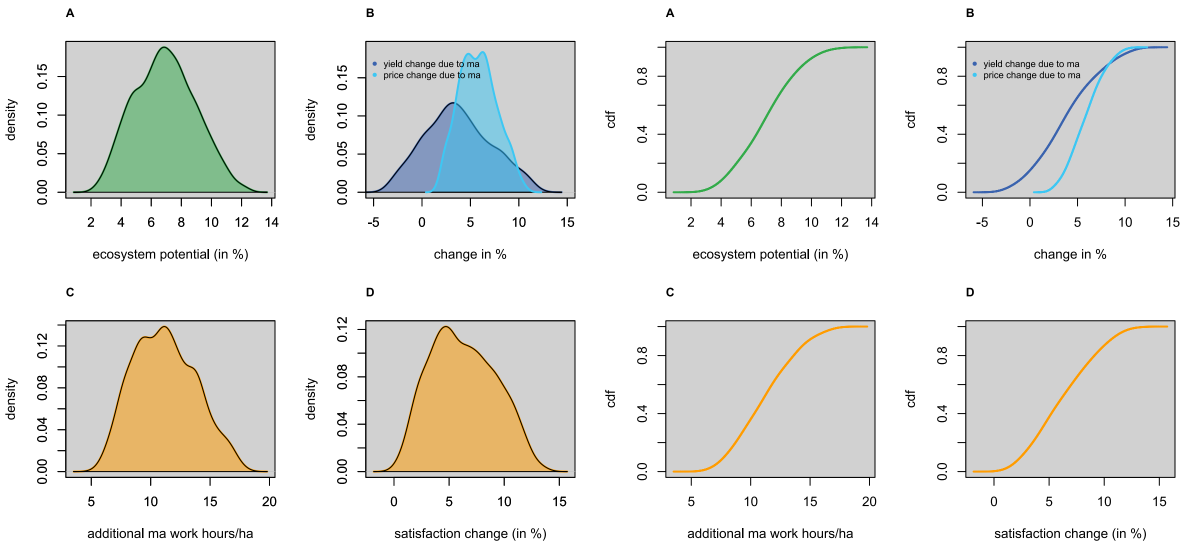
(b) Cumulative distribution function (cdf)

Fig. 5.31: Densities and cumulative distribution function of expert estimated production inputs.

ten times the industry prices. The experts are more optimistic about future prices. They expect prices to drop by about €50 kg^{-1}, which is still far from current industry prices for microbial applications of €33.80 kg^{-1}. The experts disagree more on current than on future prices, as indicated by the larger standard deviation and larger confidence intervals of the current price estimates as compared to the future price increase estimates.

According to the experts, the probability that Nitrogen (N), Phosphorous (P) and Potassium (K) fertiliser inputs can be reduced by 10% to 20% through microbial applications is 50%, 62% and 23% respectively. By contrast, an NPK increase is reported by 0.5%, 21% and 30% respectively in the SIMBA farmer survey. Notably however, both the farmer sample and the current expert sample are small. We found no data in literature that can reliably validate these findings in the context of Dutch potato farming. Some authors claim to have found a reduction, but do not quantify the reduction effect and/or the studies have been conducted in a different geographical context (e.g. Trabelsi et al. (2012)).

In the SIMBA farmer survey, farmers that apply microbials use 28% fewer PPP than non-adopters. However, individual PPP have not been differentiated. Compared with the expert elicitation results, experts underestimate the PPP reduction potential of microbial applications. The experts see the largest PPP reduction potential with fungicides. Accordingly, there is a 15% probability of reducing fungicide use by 10% to 20%. These findings are in line with the validation data in Orlando et al.



(a) Densities (b) Cumulative distribution function (cdf)

Fig. 5.32: Densities and cumulative distribution function of expert estimated production outputs.

(2020). However, Orlando et al. (2020) also state that the biggest problem in potato cultivation are nematodes, which cannot be reduced with biocides. In addition to the fertiliser and PPP reduction potential of microbial applications, experts quantify a potential increase of ecosystem health by 6.92%. Potential ecosystem health effects include impacts on biodiversity and soil health, and have been mentioned during the expert elicitation workshop.

Moving from production input variables in Figure 5.31 to production output variables in Figure 5.32, we see that, on average, yield is expected to be increased by nearly 4% with a rather narrow confidence interval ($[3.52, 3.94]$). A 4% increase per hectare is a substantial increase. However, there is a 15% probability that yield decreases with microbial applications according to the experts. The possibility of a yield decrease is confirmed by the SIMBA farmer survey data in which adopters have about 2.4% lower yield per hectare than non-adopters. Yet, according to the industry information, consumption and seed potato farmers who adopted microbial applications experience yield increases by 3.9% and 7.5% respectively. Our experts' estimates are close to these industry claims.

In the validation literature, we find a wide range of yield increase claims, much larger than the experts' estimates. However, in most studies the control is not conventional crop production, but production without fertiliser and PPP use. Therefore, the yield gains in literature cannot be compared directly with our data.[2]

In literature it is assumed that microbial applications suppress plant diseases and control pathogens (Gouda et al. 2018). According to our expert panel, on average, prevalence of diseases is reduced by 0.22%. However, there is a 47% probability that the prevalence of diseases even increases.

5.3.2 Simulation Results

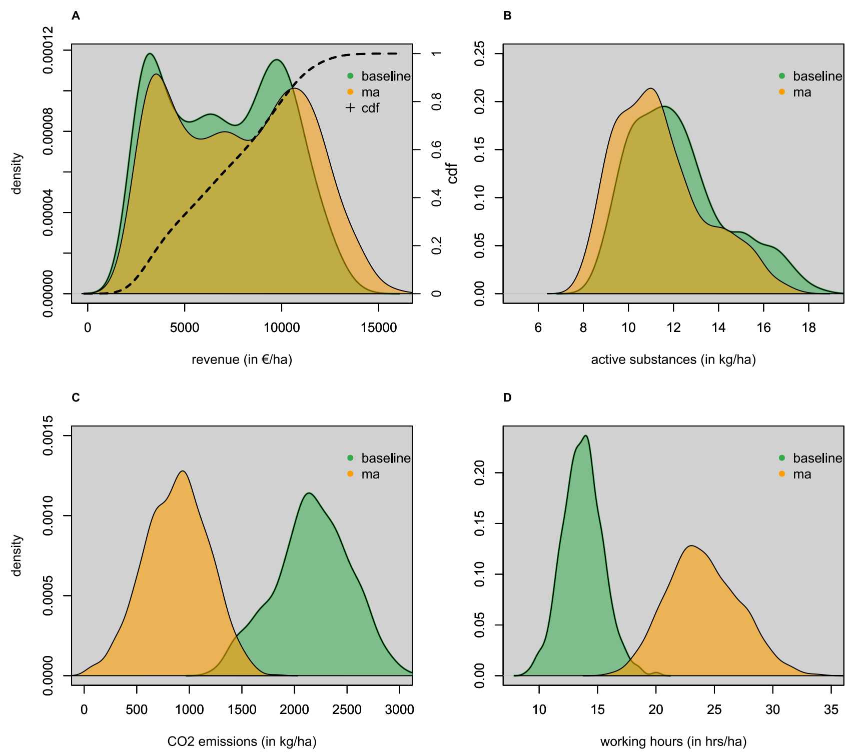


Fig. 5.33: Selected simulation outputs comparing baseline and microbial application scenario.

[2] We report the findings for completeness: The biggest potato yield increase has been found by Belimov et al. (2015) in field experiments with rhizobaceria. They have found a potato yield increase of up to 27%. Yield increase is caused by an increase in the number of tubers rather than by an increase of tuber weights. The authors conclude that the rhizobacteria accelerate vegetative development. Mülner et al. (2020) report a 24% yield increase and Larkin (2016) find an increase average between 11% and 15%. Buysens et al. (2016) have investigated the impact of a rhizobacteria application to a cover crop preceding potato planting and to potatoes directly and find a 6.9% yield increase.

Revenues in the baseline and microbial application scenario are based on the same yields and price distributions. The resulting revenue density distribution is bipolar because of differences in yields and selling prices of the different potato products (see Table 5.21), which are pooled in Figure 5.33 panel A. Average yield is 44.08 tonnes ha^{-1} in the baseline scenario and 45.63 tonnes ha^{-1} in the microbial application scenario (+3.7%) across potato products as visualised in Figure 5.34. Average selling price is €16.75 for 100 kg of potatoes in the baseline scenario and €17.73 in the microbial application scenario. As a result of the increase in potato yield and selling prices, we find a 9.8% higher revenue in the microbial application scenario with an average of €7,714 ha^{-1} compared to €7,027 ha^{-1} in the baseline scenario.

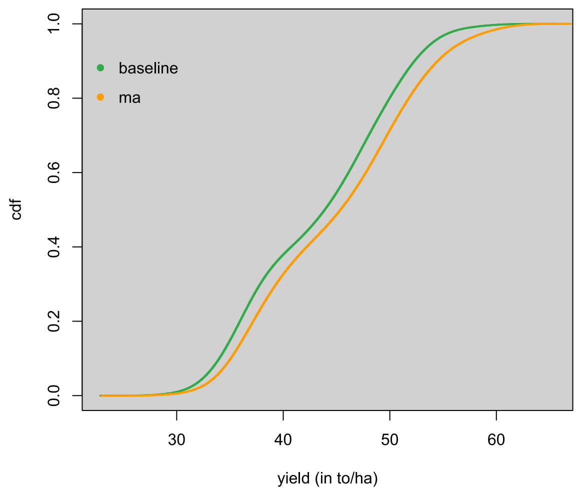


Fig. 5.34: Cumulative Density Function (CDF) of simulated baseline and microbial application potato yield.

Costs in the microbial application scenario are a multiple of the costs in the baseline scenario (see Figure 5.35). The substantial differences are caused by high estimated costs and dosages in the microbial application scenario. The high costs for microbial applications and high indicated dosages are not compensated for by reduced fertiliser inputs and even less by increased yields or reduced PPP. On average, the costs are €591 ha^{-1} in the baseline scenario, and €15,994 ha^{-1} in the microbial application scenario! Even if we factor the costs for CO_2 emissions in, microbial applications are not cost-effective in the current study. One ton of CO_2 is traded at around €63 in 2022. Accordingly, the costs in the baseline scenario would be about €130 higher but still far from the costs in the microbial application scenario. In both models, costs consist of variable inputs only.

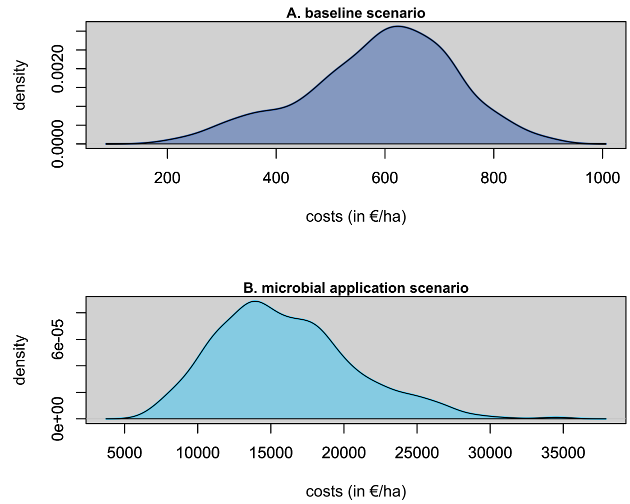


Fig. 5.35: Simulated costs of production in baseline and microbial application scenario.

5

Labour hours, which are considerably higher in the microbial application scenario (see Figure 5.33, panel D), are excluded.

Besides labour hours, farmers' satisfaction is used as a social indicator and we assume that baseline farmers have a mean satisfaction index of five with a standard deviation of one. Farmers in the microbial application scenario have a slightly higher satisfaction index with an average of 6.28 and a large standard deviation of 2.92. The Welch two-sample t-test reveals that there is a statistically significant, but small difference between the satisfaction indices of the two production systems. Experts argue that farmers might be more satisfied because they believe that this farming practice is better for the environment, improves soil quality in the long run as well as yield and product quality. All qualitative expert answers are provided in 5.6.

Overall, we see the largest improvement with the environmental indicators (Figure 5.33, panel B and C). According to the experts, PPP use is slightly reduced when microbial applications are adopted which leads to a 6.6% reduction of active substances. Fertiliser reduction is substantial when microbial applications are adopted which leads to an almost 60% reduction of CO_2 emissions compared to the baseline scenario. The probability that the CO_2 emissions are the same in both scenarios is only 14%. Since this is the first study investigating environmental and social effects of microbial applications, there are no validation data available for these findings.

5.3.3 Sustainability Analysis

Comparing the two different weighting methods to aggregate the sustainability index (the BoD approach and expert weighting) shows that the BoD ci is more favourable than the subjective expert-weighted index. There is almost no difference in BoD scores in the baseline scenario between the different potato crops but a large difference between the potato crops in the microbial application scenario (see Figure 5.36). In the latter scenario, seed potatoes are more sustainable than both consumption and starch potatoes. The range of the sustainability indicator in the microbial application scenario is larger than in the baseline scenario, because we introduce additional variability in the MC simulation model.

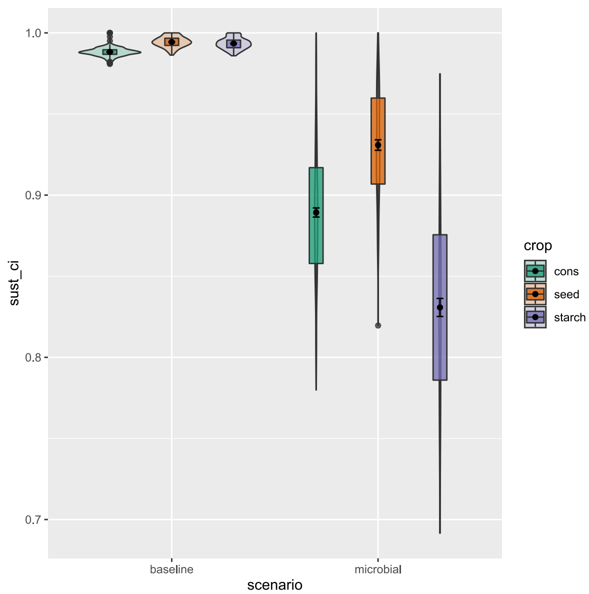


Fig. 5.36: Boxplot sustainability indicator in baseline vs. microbial application scenario.

The BoD approach allows to explore single indicator weights. Since these weights are endogenously determined, they reflect how much each decision-making unit trades-off one attribute for another. Accordingly, the most important sustainability dimension for all three potato products is the environmental one. CO_2 emissions are the most important single indicator, followed by income and costs, which are the two indicators from the economic dimension. Large costs decrease the sustainability performance of the microbial application scenario.

The microbial application scenario has an average sustainability index of 0.81 and can thus be considered sustainable. Six out of thousand observations have a sustainability index larger than

0.99. The baseline scenario has an average sustainability index of 0.99 with 429 observations having an index larger than 0.99. When comparing the sustainability index of the baseline scenario and the microbial application scenario, we conclude that to date potato production without microbial applications is more sustainable than production with microbial applications. We want to stress that the sustainability indicator is not an absolute measure of sustainability, but a relative estimate of sustainability, comparing one system with the other. Two-sample t-tests reveal that the composite indices are significantly ($p < 0.001$) different. The adoption of microbial applications at their current state, as described by experts, could reduce the sustainability of Dutch potato production. The results hold under the different robustness checks.

5.3.4 Sensitivity Analysis

Figure 5.37 shows the effect of a change in the model inputs on the model outputs and the aggregated sustainability index. In the two top rows, the baseline and the microbial application scenario are depicted. All other boxplots visualise sensitivities. The social indicators (working hours and satisfaction) are not affected by the changes applied in the sensitivity analyses, but are included in the figure for completeness.

Generally, the effect on the model's outputs (revenue, costs, active substances, CO_2 emissions) is most notable when the changes in the model's inputs (effectivity in terms of yield increase, PPP and fertiliser decrease; price changes) are large. For instance, when effectivity in terms of fertiliser and PPP reduction or yield increase potential is raised by 50%, there are visible impacts on the single indicators and also on the composite sustainability index. The microbial application scenario becomes almost as sustainable as the baseline scenario when the fertiliser reduction potential of microbial applications is increased by 50% (Row 8 in Figure 5.37). The experts report a NPK reduction potential of 20%, 12% and 26% respectively, but the sensitivity analysis shows that an NPK reduction of 70%, 62% and 76% respectively is needed to enhance the sustainability of the baseline production system. Likewise, the microbial application scenario with industry data (Row 17 in Figure 5.37) is as sustainable as the baseline scenario.

From the visual analysis, we conclude that microbial applications can have a considerable CO_2 reduction potential when fertilisers can be further reduced by their usage. More effective microbial applications also have a potential to reduce active substances. Through lowering the environmental footprint, overall sustainability increases of the potato production system with microbial applications can be achieved. Like effectivity improvements are a necessary condition for environmental sustainability, cost reduction is a necessary condition for economic sustainability. A combination of multiple improvements of microbial applications is the only way to increase the sustainability of potato production through microbial applications including lower costs and higher effectivity.

The two-sample t-test results confirm the findings from the visual analysis. The baseline scenario ($\mu = 0.99$) would still be significantly ($p < 0.001$) more sustainable than the microbial application scenario ($\mu = 0.81$), even if fertiliser prices tripled or PPP prices increased by 10%.

5.4 Discussion

In this study, we assess the capacity of microbial applications to enhance the sustainability of primary food production systems. Our research question is targeted at the sustainability of Dutch potato production. Results show that microbial applications, as described by the experts, are not yet up for the task. To date, microbial applications are not effective enough in reducing the need for PPP and are not expected to bring adopting farmers closer to the 50% reduction goal of the Farm to Fork strategy. Since farmers need a product that helps them to reduce the amount of PPP and microbial applications fail to do so, we conclude that to date microbial applications cannot - as a single measure - improve the sustainability of Dutch potato production. However, the sensitivity analyses show that an increase of effectivity of microbial applications can improve the overall sustainability of potato production.

We provide insights into the advantages and disadvantages of using microbial applications in a primary crop production system. The major advantages of microbial applications are their yield increase potential and their positive effect on the environment by reducing CO_2 emissions and active substances. However, there may be other beneficial environmental effects, such as ecosystem services and effects on biodiversity (Arif et al. 2020). These environmental effects are usually difficult to measure. Another advantage is the additional satisfaction that a farmer receives when using microbial applications and fewer harmful substances.

In this study, we found two main disadvantages. First, the costs of microbial applications, as estimated by the experts, exceed the benefits. The high costs are not compensated by input reductions. Considering that about 40% of the Dutch arable farmers are operating below minimum income levels (Berkhout et al. 2022), the cost increase simulated in the microbial application scenario is infeasible for the majority of farmers. Second, the effects of microbial applications are highly uncertain. As the yield increasing effects are not stable, nor guaranteed, farmers will not take the risk of paying a high price for microbial applications nor of reducing their use of fertilisers and PPP. Currently, the main biotechnological challenge is to develop a low-cost, effective and stable microbial application (Romano et al. 2020). Further, we find that the prevalence

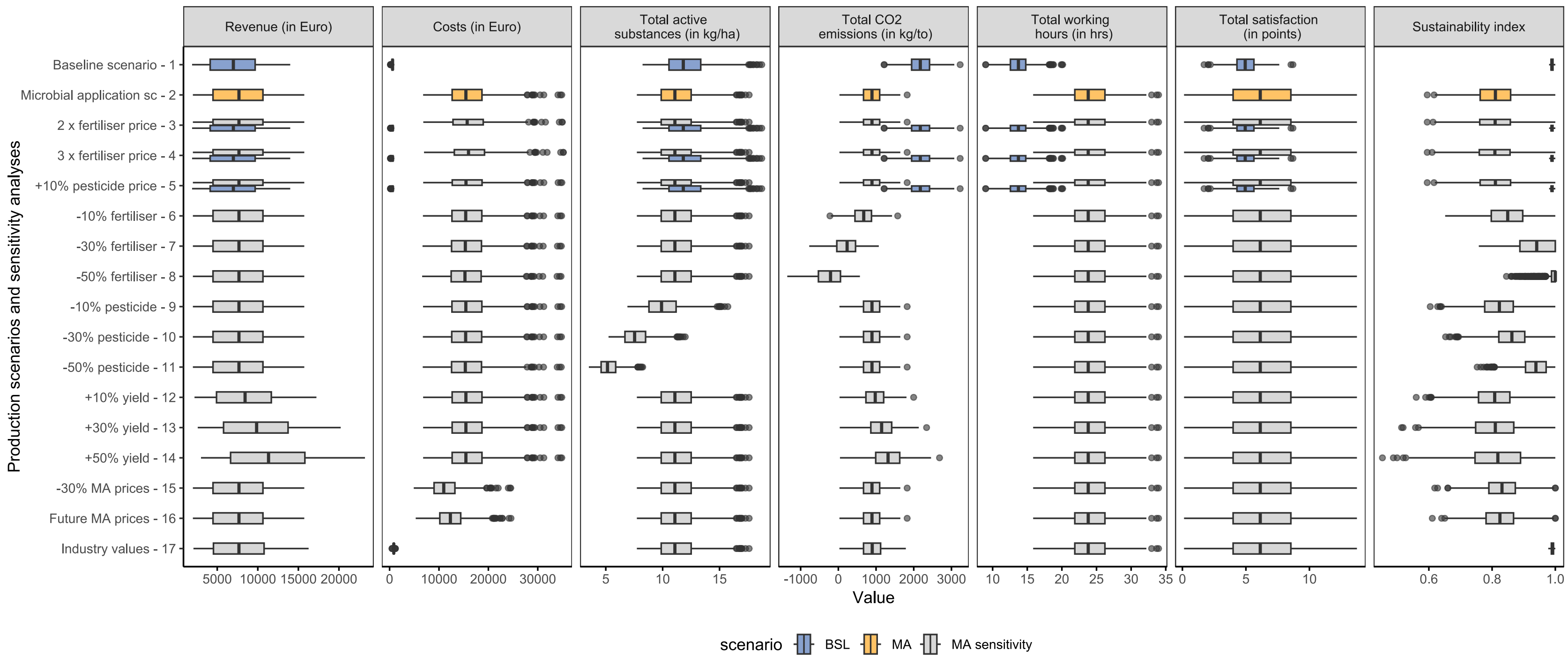


Fig. 5.37: Box plots comparing baseline and microbial application scenarios (row 1 and 2), and all sensitivity changes: Row 3-5 fertiliser and PPP price changes in both scenarios, Row 6-8 higher fertiliser reduction potential of microbial application, Row 9-11 higher PPP reduction potential, Row 12-14 higher yield increase potential, Row 15 and 16 different microbial application prices, Row 17 industry values *Note*. 'Pesticides' refers to all PPP, but for visual purposes the shorter term is used. The three potato crops are pooled.

of diseases is most likely not reduced by microbial applications. Therefore, also the risks posed by nematodes and *Phytophthora* are unlikely to be alleviated by microbial applications. According to a study, nematodes can reduce yield by 23% to 30% in the Netherlands (Orlando et al. 2020). If microbial applications were a reliable solution for prevalent pests and diseases, their uptake would be stimulated.

Throughout this study, we compare the microbial application scenario with the baseline scenario. The baseline scenario reflects the current production situation of potatoes in the Netherlands. However, one can question whether this is the correct baseline. On the one hand, if PPP lose their license of operation and farmers are forced to use fewer fertilisers to reduce nitrogen and phosphorous concentrations in surface waters, the baseline should be a clean control. We would want to compare the microbial application scenario with a control scenario without the use of PPP and fertilisers. On the other hand, currently, farmers can only be convinced if microbial applications are competitive in all sustainability dimensions. Then, the baseline should reflect the current production situation, as is done in this study.

This simulation study is based on expert information to fill gaps in knowledge from literature and industry. Expert elicitation is commonly used to gain insights in data-scarce environments (Martin et al. 2012) and to integrate different disciplinary views (Janssen and Goldsworthy 1996). Expert elicitation results have been found to be consistent with literature and can be an alternative to existing data-rich methods but might be less reliable for novel systems (Pashaei Kamali et al. 2017). Nevertheless, Delphi expert elicitations have been conducted to collect data on novel agricultural systems *ex-ante*. For example, Jones et al. (2017) investigated the agro-economic benefits for farmers and consumers of certain genetically modified crops. Torgerson et al. (2021) applied the Delphi method to explore to what extent the by-products of insect production could be used as a crop and soil health promoter. Gardner et al. (2021) identified novel crops for south-west England with a Delphi method and showed that the assessment of an expert panel can be used in crop suitability models.

Our findings from the Delphi expert elicitation and the validation data are not always in line. The experts overestimate current dosage and market prices, which could be a consequence of the panel composition. As most experts are researchers, they may not have correct pricing information on the current market situation. However, as the effects reported in literature are not always reliable either (Kołodziejczyk 2014), and considering the data scarcity on microbial applications, the expert elicitation provide valuable insights and novel data. The expert elicitation confirms that the effects of microbial applications are uncertain. This highlights the need for reliable, replicable research on the effects of microbial applications.

Several studies suggest that experts with commercial interests should not partake (Ehlers et al. 2021). However, we deliberately chose to include industry representatives for their knowledge on marketed microbial products. By including industry experts, we have also intended to alleviate scientists' trained "T-focused" bias. The T-focused bias makes scientists prone to be too optimistic in the short term. They feel that an innovation is feasible and therefore will be implemented, but underestimate the organisational or other non-technical difficulties that may impede implementation and market uptake (Linstone and Turoff 2011).

The MC simulation model used in this study is a simple, stochastic model. MC simulations are a common tool to assess *ex ante* environmental and economic impacts of novel technologies. For example, Tillie et al. (2014) simulate the impacts of adopting genetically modified herbicide tolerant maize on farmers' gross margin with a stochastic partial budget model. Mavrotas and Makryvelios (2021) combine a multi-criteria analysis, mathematical programming and MC simulation to assess the uncertainty in research and development projects.

Another prominent modelling approach is the combination of crop models with economic models. Such bio-economic simulation models are used to evaluate the economic viability of risky crop management practices (Kadigi et al. 2020) or soybean cultivation in lowland rice systems in southern Brazil (Ribas et al. 2021). Examples for famous crop models used in bio-economic modelling (see Britz et al. (2021) for a review) are *FarmDESIGN* (Groot et al. 2012), *FarmDyn* (Britz et al. 2016) and *CropSyst* (Stockle et al. 1994). With these models, the consequences of crop management decisions on yields and other farm performance indicators can be calculated (Kuhn et al. 2022; Mandryk et al. 2017). However, these models do not consider economic incentives (Lehmann and Finger 2014) or environmental and social indicators and are focused on farm management decisions, which is not the focus of this study.

At the current state of development of microbial applications, the available information and data restrict the use of pre-existing models. Pre-existing bio-economic and crop models are often very detailed, and the necessary input data on the effect of microbial applications are missing. With limited reliable information and data, uncertainty increases with complexity. Simpler models are suggested to produce more accurate predictions, while larger models are more difficult to falsify, in particular when the input parameters are uncertain (Puy 2022; Puy et al. 2022). Therefore, our study uses a simple model with more generic input parameters.

5.4.1 Limitations and Further Research

First, the system boundary of the model, the farm gate, does not allow a comprehensive cradle-to-grave analysis. Once further information is available, the system boundary should be widened because the environmental footprint of the large-scale production of microbial applications is expected to be substantial. However, even when life cycle greenhouse gas emissions of microbial application production are as high as the emissions of producing PPP and fertilisers, microbial applications have the potential to improve the sustainability of primary production systems.

Second, we introduce uncertainty distributions on the parameters, but we do not model interaction effects due to a lack of knowledge as to how the variables exactly interact. It is unknown how microbial applications biophysically affect plant growth and resilience. Therefore, a bio-economic modelling approach could not be implemented. Our suggestion for further research is to investigate the biophysical pathways of microbial applications affecting plant growth and resilience. This knowledge would enable a bio-economic modelling approach by integrating microbial application effects, and economic and social indicators into crop models such as LINTUL (Haverkort et al. 2015; Kooman and Haverkort 1995), WOFOST (Den et al. 2022) or FAO Aqua Crop (Razzaghi et al. 2017). In such an extended model, the survival time of microbial applications in the soil, amongst others, could be taken into account to turn the model into a dynamic model. With the survival time of microbial applications long-term effects of microbial applications on ecosystem services and biodiversity can be modelled.

A third route for further research is the inclusion of different production scenarios. In addition to comparing the microbial application with the baseline scenario, it could also be investigated how the two production systems behave under different climate change regimes or under salt stress. For instance, the study of Raymundo et al. (2018) provides valuable information for modelling a baseline saline potato production scenario. In this extension route, a clean control baseline scenario could be introduced, too.

The simulation model input data is further limited by the small number of experts in the panel. Even though there are sixteen experts, we only record five and ten answers in the two Delphi iterations respectively. Nonetheless, we have not invited additional experts. The panel has been coherent and an increase in group size could have lead to compromises such as inviting new experts that do not fit the group and/or do not have sufficient expertise (Pashaei Kamali et al. 2017). As the microbial application dosage and prices have been far off from industry values in round one, we have eliminated the possibility that the experts misunderstood the question by highlighting the units in the last iteration. Further, there is a reasonable explanation for the large difference between expert estimates and current industry dosages: Researcher are aware that much larger amounts of microorganisms than recommended by manufacturers need to be applied to the soil, as they need to compete with a large mass of soil microorganisms (Kołodziejczyk 2014). This awareness could explain experts' estimates. A natural progression of this work would be to repeat the Delphi study with another group of experts, if other experts are available.

5.5 Conclusion

We have conducted a Delphi expert elicitation, modelled a Dutch potato production system with and without microbial applications with MC simulation, and computed a comparative composite sustainability index. Through the expert elicitation we have provided novel data on the effects of microbial applications. In the simulation model, we have quantified microbial application effect uncertainty. Employing the composite sustainability index, we have assessed the capacity of microbial applications to enhance the sustainability along environmental, economic and social dimensions, of the Dutch potato production system. Overall, we find that a potato production system that incorporates microbial applications can be sustainable. However, our comparative composite sustainability indicator shows that microbial applications are not (yet) able to enhance the sustainability of the Dutch potato production system.

To answer the research question how microbial applications affect the sustainability of Dutch potato production, we have presented advantages and disadvantages of microbial applications. We find three main disadvantages. First, due to their very high costs, microbial applications are to date not financially viable. Second, in line with previous studies, we find that the size effect of microbial applications is uncertain and variable. Third, our experts do not confirm the assumption that microbial applications can be a reliable solution to alleviate diseases. Nonetheless, there are two main advantages. The effect of microbial applications on environmental sustainability is expected to be positive, indicated by almost 60% lower CO_2 emissions and 6.6% fewer active substances. Additionally, microbial applications are expected to increase yield by 3.73%.

Our study suggests environmental gains, albeit at a high economic cost. Technological advancements are required to further reduce the costs per unit of production and increase environmental sustainability. In this way, microbial applications can be part of the solution to enable the sustainable transformation of agri-food systems.

5.6 Appendix

Calculating Dutch Farm to Fork goals

Table 5.61: Calculating baseline use of fertilisers and PPP in Dutch arable farming and Farm to Fork reduction goal.

Use of active substances		
year	$kg\ ha^{-1}$	
2015	8.19	
2016	9.4	
2017	8.6	
average	8.73	
Farm to Fork goal	4.36	
2020	9	
N fertilisation		
year	$kg\ N\ ha^{-1}$	
2015	124	
2016	122	
2017	115	
average	120.33	
Farm to Fork goal	96.26	
2020	101	
Phosphate fertilisation		
year	$kg\ P\ ha^{-1}$	
	Kunstmest	Dierlijke mest
2015	10	42
2016	10	42
2017	9	43
average	9.67	42.33
Farm to Fork goal	7.73	33.87
2020	8	40

All data from Wageningen Economic Research (WEcR) (2022) on arable farming in the Netherlands.

Literature review

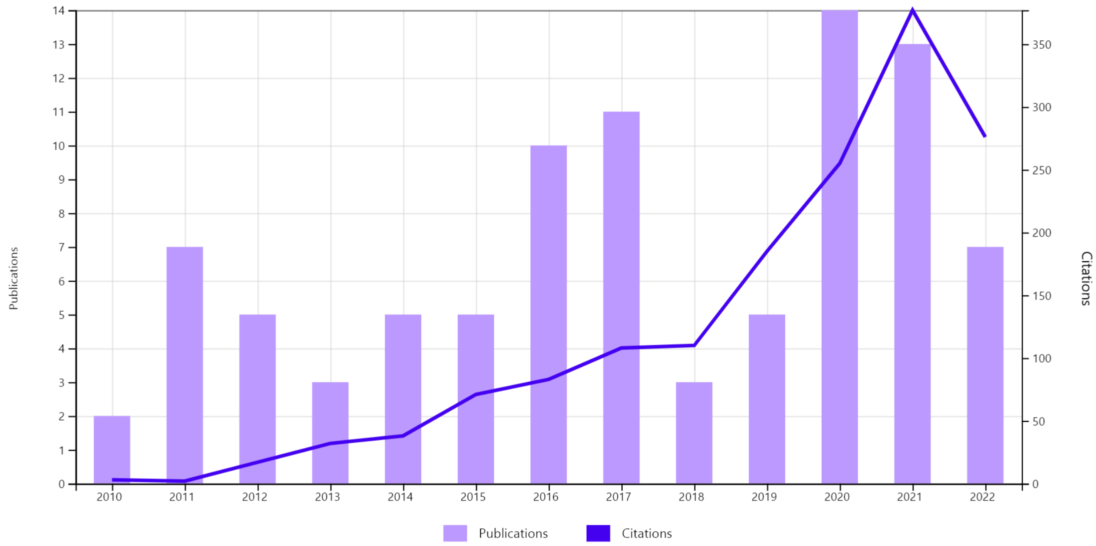


Fig. 5.61: Number of citations in Web-of-Science with search term.

In the Web-of-Science literature review, we used the following search term for the time-frame from 2010-01-01 to 2022-11-01:

AB = (potato) AND AB = (plant growth promoting rhizobacteria) NOT PUBL = (Mdpi) NOT ALL = (processing) NOT ALL = (pakistan) NOT ALL = (india) NOT ALL = (china) NOT ALL = (sweet)

OR

AB = (potato) AND AB = (microbial applications) NOT PUBL = (Mdpi) NOT ALL = (processing) NOT ALL = (pakistan) NOT ALL = (india) NOT ALL = (china) NOT ALL = (sweet)

In the Google Scholar literature review, we used the following search terms for the same time-frame as above:

potato "microbial applications" -processing -pakistan -india -china -sweet source: -MDPI

potato "plant growth promoting rhizobacteria" -processing -pakistan -india -china -sweet source: -MDPI

We excluded studies that have been published in MDPI (Multidisciplinary Digital Publishing Institute) journals because it is already difficult to judge which studies on microbial applications we can trust (Kołodziejczyk 2014), and “[s]tudies published in predatory journals often have a lower quality and are more likely to be impacted by fraud and error compared to studies published in traditional journals" (Munn et al. 2021). Predatory journals are characterised, amongst others, by deviating from best editorial and publication practices and false or misleading information (Grudniewicz et al. 2019), and MDPI is identified as such a predatory journal (Ángeles Oviedo-Garciá 2021).

In total, the search delivered 90 publications that have been cited 1,559 times. A list of the 90 publications and their inclusion/exclusion criteria is presented in the table below. The publications have an H-Index of 21. When MDPI has been excluded in the search, there have been ten publications more. When MDPI and the countries have not been excluded, we obtained 149 publications.

Qualitative Results Farmer Satisfaction

In the second expert elicitation round, we asked the experts to explain why and how they think farmers' satisfaction might change upon the adoption of microbial applications. The **raw** qualitative answers are provided below.

- The farmers are satisfied when using microbial application either as biofertilizers or biopesticides compared to the baseline, but the inconsistent efficacy of such products impacts their larger adoption. Unfortunately, the farmers usually use the easily accessible agrochemicals to obtain more stable results.
- May be better yiel[d] and quality
- The feeling of doing something better for the environment - and presumably better performance
- Obtaining a higher yield with a reduction of inputs
- Improving soil quality in the long term
- Contribute to sustainable agriculture and environment care
- The farmer no longer uses pesticides and produces healthier food
- Farmers are more aware of the "negative" impact of traditional, non biological farming (e.g. using fertilizers and herbicides) on nature and how it resonates in EU policies. In that respect they surely are looking for improvements and change and I think they will be willing to try novel, improved methods as long as it is profitable. Being able to be not part of the problem but part of the solution will lead to greater satisfaction.
- Farmers are more receptive to the use of inoculants mainly because high-quality products available at the market, improving yields at low cost in comparison to chemical fertilizers.

Chapter 6

General Discussion

Against the backdrop of environmental degradation, climate change, population pressure and supply chain disruptions, the need for sustainable farming becomes more apparent. Agricultural innovations support the transition towards sustainable agri-food systems. Microbial applications are an example for a potentially sustainable innovation. Microbial applications serve as an environmentally friendly supplement or substitute for Plant Protection Products (PPP) and fertilisers by alleviating abiotic stresses, strengthening crop resilience, and supporting plant growth and quality. As agronomists and plant scientists continue to improve microbial applications' effectiveness, this thesis analyses microbial applications from a social science perspective. More specifically, the objective of this research is to investigate the uptake and effects of sustainable innovations in general, and microbial applications as an example, from a farmers' perspective.

This thesis provides four research chapters in which distinct, yet connected objectives are addressed. In each chapter, different methodological approaches are used to investigate uptake and effects of sustainable innovations, as well as their impacts on sustainability. The research chapters provide insights into the field of production and behavioural economics, and sustainable agricultural practices. I investigate the effect of innovation processes on farm performance *ex post* (Chapter 2), and of a sustainable innovation on sustainability of a farming system *ex ante* (Chapter 5). Behavioural factors and interventions for the uptake of a sustainable innovation are investigated (Chapter 3 and 4). I mainly focus on Dutch arable farmers, and in three out of the four chapters, specifically on microbial applications as an example for a sustainable innovation. The main contribution of the research chapters are insights into the uptake factors and sustainability effects of microbial applications. The research informs microbial application producers and developers on how to improve the products, and offers recommendations to suppliers, advisers and policy makers on how to stimulate adoption. The main methodological contribution of the research chapters concerns the conceptualisation of innovativeness in Agricultural Innovation Systems (AIS) by using composite indicators. Additionally, this thesis exemplifies *ex ante* innovation research, investigating adoption and effects of an innovation before its market uptake. *Ex ante* assessments can steer holistic evaluations and provide prior information on uptake and effects to stakeholders.

In the remainder of this General Discussion section, I first briefly summarise each research chapter. Second, I explore three synthesis themes. The synthesis is followed by a theoretical and philosophical contemplation of agri-food systems transitions. This section is broader and goes beyond what has been researched in the four chapters. Third, policy and business implications are provided. Fourth, I reflect on the materials and methods used in this thesis and avenues for future research. Last, the main conclusions of this thesis are provided.

The first research question is: What is the relationship between farmer innovativeness and farm efficiency? I address this question in Chapter 2. Results show that innovativeness is not related to farm efficiency, and farmers' innovativeness is not associated with an increase in long-term efficiency. There are two potential explanations for these findings. First, with the innovation index, I do not assess knowledge enhancements that go along with the innovation process. Potentially, innovative farmers are heterogeneous regarding the innovation accompanied learning and education, which could explain different effects on efficiency. Second, with my innovation index, I do not assess the institutional and political setting. Potentially, a lack of socio-political support impairs the translation of innovativeness into efficiency gains.

Chapter 2 provides a novel composite indicator to measure innovativeness. The innovation index consists of five single indicators. The aggregation of these five indicators allows to measure innovativeness in the sense of complex AIS. Thereby, I extend the innovation index proposed by Läpple et al. (2015), which has been used as a basis. In Chapter 2, the innovation index has been applied to Dutch arable farming. Yet, the single indicators provide a flexible framework to investigate the innovativeness of farmers regardless of the farming system or country. I provide suggestions on how to improve the data collection of national innovation monitors in the context of FADN data collection.

The second research question is: What are farmers' behavioural drivers and barriers to adopt microbial applications in arable agriculture? I address this research question in Chapter 3 using the Behavioural Change Wheel (BCW) and its Capability, Opportunity and Motivation-Behaviour (COM-B) approach. I find that trust in microbial applications is an important driver and the lack of knowledge and professional support are barriers for the adoption of microbial applications. Based on the behavioural findings, I recommend three intervention strategies. First, the use of microbial applications needs to become the norm instead of an exception, e.g. through awareness campaigns and a supportive environment removing the physical opportunity barrier. Second, education and learning are crucial for the actual uptake. It is recommended to involve advisers and extension services and to engage in peer-to-peer learning. Thereby, capabilities are strengthened and turned into drivers. Third, trust and incentives motivate the adoption. Trust can be created through large-scale and long-term field studies under realistic conditions.

Chapter 3 uses the BCW model to investigate drivers and barriers of innovation adoption and recommend interventions at the same time. Translating behavioural drivers and barriers into effective interventions can foster the uptake of sustainable innovations and farming practices in general and of microbial applications in specific. Successfully promoting the uptake of such sustainable innovations eventually allows achieving Farm to Fork targets, as defined by the European Commission (European Commission 2020b), and food security. The BCW has not been used in the context of agricultural innovation adoption before. While the BCW provides a comprehensive framework to connect behavioural factors and interventions, several shortcomings of the methodology are observed as well. The BCW and its COM-B model require a fine-grained, labour- and resource-intensive process, which is difficult to execute in practice and to apply in semi-quantitative online surveys.

6

The third research question is: How to stimulate risk-averse farmers to adopt a sustainable innovation? I address this research question in Chapter 4. I use microbial applications as a case study, assess the risk aversion of farmers and investigate the stimulating effect of an informational video. I find that this informational video has a stimulating effect on the stated uptake of microbial applications. Further, I find that risk-averse farmers are less likely to adopt microbial applications.

In Chapter 4, insights on how to promote innovation uptake are provided. Further, the results confirmed previous findings on the relationship between risk attitudes and innovation adoption. I also contribute to the behavioural economics discussion on utility modelling. I show that structural modelling approaches do not always allow to investigate risk attitudes of subjects. In my case, the model did not converge. There can be multiple reason for this. For instance, it is possible that not all individuals can be described by the same utility model. The finding that informational videos stimulate the adoption of microbial applications is the main practical contribution of this chapter.

The fourth research question is: How do microbial applications influence the sustainability of Dutch potato production? I address this research question in Chapter 5 using a Monte Carlo (MC) simulation model. To close data gaps on microbial application effectiveness and use, a Delphi expert elicitation has been conducted. The experts' judgements are used to simulate a potato production system with microbial applications. I compare this microbial system with a conventional Dutch potato production system and compute a sustainability index to compare the two systems with each other. I find that – at current effectivity and price-levels – microbial applications used in Dutch potato production cannot enhance agri-food sustainability.

With Chapter 5, I contribute to the literature by providing first insights and data on the effects of microbial applications on all three pillars of sustainability. To the best of our knowledge, this is the first *ex ante* study quantifying the on-farm sustainability gains and losses of implementing microbial applications in arable farming. Further, the results contribute to an understanding of the implicit uncertainty of microbial application effects. Although effect uncertainty has been mentioned in other studies, here, effect uncertainty is explicitly quantified as a core element in the model.

6.1 Synthesis of Results

6.1.1 Innovative Systems

In this thesis, farm innovation is conceptualised beyond the mere adoption of new on-farm technologies including also the development and diffusion of novel technologies and practices. Further, innovation processes are conceptualised as non-linear, multi-actor processes, with a focus on the role of farmers within AIS. Besides, suggestions on how extension services, advisers and farmer organisations can support innovation processes are provided. In this section, I take a broader look at these actors and their roles within innovative systems.

Previous research finds that groups of farmers exchanging information about innovation practices would only enhance innovation processes if external inputs were provided (Dolinska and D'Aquino 2016). Chapters 2 and 3 support these findings. In Chapter 2, I find that experts do not regard farmers as pioneers in developing and initiating innovations. Thus, peer-to-peer exchange alone does not make an innovative system. Instead, cooperation needs to transcend actor-boundaries. Intermediaries such as advisers can build a bridge between different actors within an AIS (Klerkx and Leeuwis 2008). For instance, a combination of extension services and social learning, such as peer-to-peer learning, has been found to support innovative systems (Genius et al. 2014; Yigezu et al. 2018). This is discussed as one of the recommended interventions, labelled as *learning and education* in Chapter 3. Learning and education generate a sense of control and may contribute to lifting adoption barriers. This does not refer to general schooling or agricultural education, but to specific training and information on the innovation in question. Farmer organisations can play a role here as facilitators of peer-to-peer exchange, possibly involving other actors such as extension services. In this way, bottom-up peer exchange can be combined with top-down extension service (Pannell and Claassen 2020).

Innovation processes induce re-organisation of farm processes and technical practices (Klerkx et al. 2012). Successful re-organisation requires learning and knowledge-based adaptation. Yet, learning does not always accompany innovation adoption (Khafagy and Vigani 2022). This further underlines the suggestion to overcome innovation uptake barriers through knowledge, education and peer-to-peer learning (Chapter 3). In Chapter 2, I conjecture that knowledge and the institutional context affect the relationship between a farmer's innovativeness and farm efficiency. Farmers in the sample might have lacked the information and knowledge to translate technological advancements into economic benefits. Consequently, I find that highly innovative farmers can be as efficient as laggards. So, to foster a successful innovation adoption, organisational resources, such as social capital and knowledge networks, need to be strengthened (Micheels and Nolan 2016).

In the conceptualisation of AIS, innovations are co-created. However, there is very limited evidence of co-creation in the investigated Dutch FADN sample (Chapter 2). Only 3% of the farmers adopted a technology developed by others. Similarly, cooperation of practitioners with developers was not observed in the context of smart farming technologies in Germany (Knierim et al. 2019) and plantain production in Ghana (Weyori et al. 2017). Also in a former study of the Dutch AIS, interactions between actors were found to be limited (Lamprinopoulou et al. 2014). The normative design of AIS with its principles of innovation co-creation, non-linear development and multi-actor approaches theoretically ensures the development of demand-driven technologies that fulfil the needs of different actors within the agri-food system (Klerkx and Leeuwis 2008).

In general, public participation in AIS is key to create socially and environmentally responsible innovation (Rose et al. 2021).

But who coordinates the interaction and interests of these heterogeneous actors? In the Netherlands, a system of innovation intermediaries has been established, which are supposed to restore innovation system interactions and coordination (Klerkx and Leeuwis 2008). Innovation intermediaries are broker organisations between two or more parties for any aspect of the innovation process (Howells 2006). In the Dutch context, innovation intermediaries take on various forms. They are publicly or privately funded, non-profit or for-profit, acting nationally or regionally, and fulfil different functions (Klerkx and Leeuwis 2009). Yet, the funding of such intermediaries is not always guaranteed (Labarthe et al. 2021). Dutch innovation intermediaries act as innovation consultants aimed at different levels of the agri-food sector, as brokerage organisations establishing peer networks or as boundary organisations connecting different actors in the agri-food sector (Klerkx and Leeuwis 2009). Such innovation intermediaries can facilitate innovations in the context of rapidly changing environments and provide windows of opportunities for innovation actors (Klerkx et al. 2010), given that their value and nature is clear to agri-food innovation actors and funding organisations (Klerkx and Leeuwis 2009).

In the context of microbial applications, the results of this thesis illustrate that a lack of knowledge and professional support are barriers for the adoption while trust can be a driver for adoption (Chapter 3). In line with their different functions described above, innovation intermediaries can remove these barriers and enhance trust in the technology.

6.1.2 Interventions to Stimulate Uptake

The key distinction between inventions and innovations is the uptake in practice. An invention becomes an innovation when adopted by its users. Sustainable farm inventions only have an impact when adopted by farmers. Given the important role of innovations in the transition towards sustainable agriculture and mitigation of climate change, their uptake is crucial (Fuglie and Kascak 2001; Herrero et al. 2020). In this section, I discuss underlying patterns of innovation uptake and intervention to motivate uptake.

In Chapter 3, I investigate behavioural drivers and barriers for innovation uptake by arable farmers with the BCW and its COM-B approach. Originally, the BCW was set up for interventions in the health and medical domain. According to Michie et al. (2008), a theoretical foundation for behavioural drivers and barriers improves the effectiveness of interventions. Their starting point was an observed gap between theory and practice as well as a lack of standardised reporting on interventions (Michie et al. 2011a). The missing link between theory and practice and the unaligned terminology led to a replication crisis: interventions that were effective in one context could not be replicated in another (Michie et al. 2009). It was not clear what made one intervention work and hindered the effect of another. Further, patterns of (unhealthy) behaviour were successfully identified but in practice these insights were not used. Interventions were designed without insights from behavioural and psychological research. As a result, interventions did not target the underlying patterns of behaviour and were not effective. From that observation came the need to not only analyse and find the roots of a certain behaviour theoretically, but also to effectively and systematically change it in practice.

Similarly, in agricultural research, farmers' behaviour has been investigated, and interventions suggested and tested. There are numerous studies on farmers' adoption behaviour of innovations, sustainable practices or reaction to policies alongside interventions. One of the most widely used behavioural theories to study farmer behaviour is Ajzen (1985)'s Theory of Planned Behaviour (TPB) or a variation thereof. TPB is mostly applied to understand and predict behaviour, but its translation to interventions is ineffective (Mullan and Wong 2010; Hardeman et al. 2002; Kothe et al. 2012) or vague (de Leeuw et al. 2015). Design and implementation of effective interventions requires an understanding of farmers' adoption behaviour (Pannell and Claassen 2020). Therefore, in Chapter 3, the BCW model was used. While the BCW is designed to facilitate transition from behavioural identification to interventions, the findings in Chapter 3 show that the model is difficult to implement in practice. In this sense, the BCW is similar to other models such as the TPB. The steps are resource-intensive and difficult to execute in practice. The limited applicability of the BCW is discussed in Chapter 3. An additional limitation is that the model does not take interventions based on behavioural economic theories, such as nudges, into account. The benefit of the BCW is its connection between the behavioural diagnosis and interventions.

One of many possible intervention strategies to stimulate the uptake of sustainable innovations is information provision. Exposure to technological information reduces subjective uncertainty and increases attractiveness (Barnes et al. 2019). The informational video examined in Chapter 4 falls under the category of informational or marketing campaigns. It can also be seen as a knowledge intervention, which has been recommended as an intervention in Chapter 3 based on the behavioural insights the study provided. As such, the informational video can be linked to 'training' and 'education' intervention functions of the BCW. The findings in Chapter 4 corroborate the beneficial effect of information provision (e.g. in Barnes et al. 2019). One of the objectives of this thesis is to define behavioural factors to adopt sustainable innovations. I find that trust in safety and efficacy of microbial applications can be enhanced through informational videos, which in turn increases adoption intentions. Further, the controlled experiment shows that farmers in the control group are less likely to adopt microbial applications than farmers that received an intervention. The statistical significance of the treatment and its magnitude suggest that informational videos can be an effective intervention to promote microbial application uptake. Depending on the set-up, production costs of such a video can be low. So, low production costs of the video can eventually compensate for a potentially uncertain real-life effect. Whether this effect materialises in practice, independent of the technology- and farmer-context, remains to be seen.

Interventions often aim to alter the perception of potential adopters (Hansen et al. 2016). Producers' perceptions play an essential role in adoption decisions (Knierim et al. 2019). Low adoption rates are related to farmers' subjective evaluation of probabilities and risks of the innovation, which hinge on farmers' exposure to information about the innovation (Feder et al. 1985). Also in this thesis, it has been found that trust in a technology is an important element for uptake (Chapter 3 and 4). As such, long-term field studies under realistic conditions can create trust through information and evidence provision (Chapter 3).

As important as the message of an intervention is its timing and its messenger (Palm-Forster et al. 2019). Regarding the timing, interventions are most effective when coinciding with political changes, such as revisions of the CAP, or farm-level changes, such as a generational change. Similarly, unanticipated shocks can accelerate innovation and technology adoption (Meemken et al. 2022). Regarding the messenger, when collecting the data for Chapters 3 and 4, an increasing scepticism against academic research institutions could be sensed in the public sphere. Further, governmental institutions are not perceived as valuable interventionists (Chapter 3). Therefore, governmental institutions should stick to classical interventions such as legislation and regulation or subsidies, or providing funding for innovation intermediaries, while softer interventions, such as information and educational campaigns should be conducted by farmer organisations, advisers and extension services. Here, the government has the role of a market facilitator (Klerkx and Leeuwis 2008). As such, different policy categories and intervention functions of the BCW (see Figure 3.7) need to be taken up by different messengers or actors.

Further, farmers need to have confidence in advisers and advisers possess up-to-date knowledge on latest farm innovations (Chapter 3). A trusting relationship between intermediaries and farmers can be created on the basis of cognitive and cultural proximity (Klerkx and Leeuwis 2008).

6.1.3 Perspectives on Sustainability on Farms and Beyond

Sustainable agriculture is based on two conceptualisations of sustainability and sustainable development: the Brundtland definition and the three pillar approach. So, sustainable agriculture ensures food security of existing and future generations, while being environmentally, economically and socially responsible. In this thesis, the focus is on the current trade-offs of the three sustainability pillars and less on the impact of farming practices on future generations. In this section, I reflect on these trade-offs in sustainable agri-food systems and how to assess them. Further, I reflect on the role of microbial applications in sustainable agri-food systems.

In Chapter 5, I assess the sustainability of a microbial application farming system in comparison to the current baseline farming system, by means of a composite index, which is weighted with the Benefit-of-the-Doubt (BoD) approach. The BoD approach, as an optimisation method, does not impose any value-laden weighting on the single indicators. Instead, the index reflects the sustainability trade-offs that are preferred by the farmers themselves. Theoretically and within bounds, a lower performance in one pillar can be compensated by a good performance in another pillar. Weight bounds set minimum requirements and maximum limits for each single indicator. In Chapter 5, bounds of the single sustainability indicators are set by expert evaluations. These bounds affect the evaluation of the overall sustainability of the respective system. The endogenously defined most important pillar in the BoD model is the environmental pillar. In other words, with the bounds set by the experts, the underlying data assign the greatest weight to the environmental pillar. And still, supposedly sustainable microbial applications do not outperform the current conventional potato production system. The (environmental) benefits do not compensate for the (economic) costs. When assessed with a BoD-based composite index, sustainability is a comparative, context-dependent concept. A farm's sustainability is benchmarked against other, comparable farms operating in similar (regulatory) environments.

By means of bound-setting, a normative desirable system can be created. Normative bounds can be set by experts, as demonstrated in Chapter 5. These bounds need to reflect sustainable landscape-level limitations. Therefore, alternatively, weight bounds can be based on theory such as the planetary boundaries (Rockström et al. 2009; Steffen et al. 2015). With well-defined bounds, the BoD approach to sustainability assessment allows for landscape level solutions, in which intensely cultivated and efficient farms operate on fertile soil, compensated by less intensely operated farms in nature areas. Aligning sustainability weight bounds with planetary boundaries can be a strategy to shift the focus of agri-food production to sufficiency and equity, while improving physical and social provisioning systems (O'Neill et al. 2018; Gerten et al. 2020).

When assessing sustainable agri-food systems, another question is where to set the spatial and analytical boundaries of the system under evaluation. In systems characterised by the Butterfly Effect, setting the spatial boundary is a non-trivial decision for sustainability assessment. The Butterfly Effect, as coined by Lorenz (2000) in 1963, refers to a situation in which small activities in close proximity can have large consequences at the other side of the world. The concept of the Butterfly Effect thus visualises the importance of choosing spatial system boundaries consciously. As such, depending on where we set the limits of the system, the results of a sustainability assessment can be very different.

In terms of analytical boundaries, in Chapter 5, I do not investigate the preceding or successive value chain, nor the cradle-to-grave life cycle of potato products or the possible system effects of microbial production on other parts of the world. For instance, the effects of the production of microbial applications compared to the production of PPP and fertilisers is not part of the analysis. This could change the comparative evaluation of microbial application sustainability. The production of PPP and fertilisers have considerable impacts on the environmental footprint of conventional production (Rockström et al. 2020). If the production of microbial applications is less environmentally detrimental than the production of PPP and fertilisers, microbial application agri-food systems can turn out to be more sustainable. In fact, this is a likely scenario as fertiliser and PPP production are known to be energy intensive and heavily GHG emitting (Pervanchon et al. 2002). However, this cannot be investigated *ex ante* due to a lack of large-scale production data on microbial applications.

In this thesis, I take on a systems approach to innovations and proclaim that innovation systems should not be technology-bound (Chapter 2). Yet, I focus on a single technology, namely microbial applications, in three out of four research chapters. Here, I want to reflect on the role of microbial applications within a system of innovative technologies and their role in sustainable arable farming.

In Chapter 5, I find that – at given assumptions and data – microbial applications cannot enhance the sustainability of Dutch potato farming. Even though microbial applications can play a role in novel agroecological crop protection systems (Deguine et al. 2023), they do not transform the agri-food system. In fact, no single technology is able to transform the agri-food system into a sustainable one alone (Nayal et al. 2021). A combination of various technologies and partial adoption of innovations is needed. Further, even if sustainable technologies are available, “stakeholders must work together to assemble the right bits into fit-for-purpose combinatorial innovations” into socio-technical bundles (Barrett et al. 2020, p. 168). For instance, given that the effectiveness of microbial applications is enhanced through research in the course of the next years, and their price is reduced, a link between microbial applications and smart farming technologies could reduce the amount of fertilisers and PPP input in production, if implemented by stakeholders. Already, a lot of potential is seen in the adoption of smart farming technologies alone (Walter et al. 2017), but negative perceptions of farmers hinder their adoption (Monteiro Moretti et al. 2023). All in all, to arrive at a sustainable agri-food system, integrated system thinking in terms of innovations, detached from silver-bullet-solution thinking is needed.

6.2 Transformations

Bold changes to the direct drivers of the deterioration of nature cannot be achieved without transformative change that simultaneously addresses the indirect drivers.

The Global Assessment Report on Biodiversity and Ecosystem Services
IPBES, 2019

This thesis is not about agri-food system transformations. However, when looking at the pressing environmental and societal issues, realising that there is no simple technological fix as described in the previous section, one recognises the need of major agri-food system transformations. The research presented in this thesis provided indications that microbial applications, as an example for a sustainable agricultural innovation, have only limited impact on farming sustainability and that their uptake is hampered by behavioural and technological factors. To achieve sustainable agri-food systems, so systems that ensure food security, foster social justice and environmental integrity now and for future generations, transformative changes in agriculture at multiple scales are needed (Skrimizea et al. 2020). In this section, a theoretical contemplation on European agri-food system transformations and the role of the Common Agricultural Policy (CAP) in such transformations is provided. Further, I engage in a philosophical thought experiment on how agri-food systems can be reinvented.

Agri-food transformations are related to the concepts of a fourth agricultural revolution and 'agriculture 4.0', which are used interchangeably. To date, there is no established definition of the fourth agricultural revolution (Barrett and Rose 2022). What is often meant with the fourth agricultural revolution is a technical revolution which transforms food production through emergent technologies. These technologies include robots, sensors, artificial intelligence, internet of things and the combination of all these technologies (Rose and Chilvers 2018). The uptake of these technologies has the potential to revolutionise agriculture and farming, changing farmers' realities, values and identities, and introducing new benefits and risks (Barrett and Rose 2022). For instance, smart farming technologies already raise all sorts of ethical (van der Burg et al. 2019), data ownership (Lioutas et al. 2019) and trust (Jakku et al. 2019) questions.

However, agri-food system transformations need to go beyond agriculture 4.0 and the adoption of innovations. Notwithstanding that these technology-induced transformations are changing farmers' life and work, technological fixes are not sufficient in the evolution towards sustainable agri-food systems. Innovation and technology adoption needs to be accompanied by a wide range of social and institutional changes, including infrastructure, skill and capability changes (Herrero et al. 2020). A sustainable transformation implies fundamental "changes in cognitive, relational, structural and functional aspects of agricultural systems" (Skrimizea et al. 2020, p. 257). In terms of functional changes, agricultural production goals need to be re-defined. Here, I closely follow the argument of Chaplin-Kramer et al. (2022). They use the term *un-yielding* to refer to a de-emphasised focus on yields alone. The authors argue that yield is merely an intermediate means to the true endpoint of human well-being. With a strict focus on yield as the only outcome of agricultural production, many other benefits, such as livelihoods, health and landscapes, move out of focus. In terms of structural changes, this includes a reform "of the values, regulations, policies, markets and governance" (Herrero et al. 2020, p. 267) of agri-food systems.

What is the role of the CAP in agri-food system transitions? The CAP's most important measure, income support, consists of the basic payment scheme and green direct payment (or greening). The basic payment scheme is connected to a set of basic rules, such as management requirements and good agricultural practices, which is called cross-compliance. Farmers are directly affected by these income support measures. The green direct payment rewards farmers who preserve natural resources and public goods through their farming practices. The other two pillars of CAP subsidies concern market measures and rural development measures.

The CAP's current role can be interpreted from two-sides. Candel (2022) argues that the CAP is still dominated by and embedded in neoclassical assumptions because food is almost exclusively conceptualised as a commodity. When seen as a commodity, the value of food is determined by markets, and policies are evaluated in terms of potential trade distortions or market disturbances (Candel 2022; Jackson et al. 2021). Moving away from the conceptualisation of food as a commodity is closely related to the idea of *un-yielding* described above (Chaplin-Kramer et al. 2022). Generally, in neoclassical economic theory, the focus is on indefinite GDP growth and GDP is seen as a welfare measure (Daly 1999). Further, markets are not supposed to be curtailed by normative restrictive measures or legislation. Instead, the *invisible hand* is supposed to steer markets to optimal equilibria. However, according to Blandford (2010), "neither a neoliberal nor a neoregulatory approach is likely to be able to solve pressing problems affecting agriculture and natural resources." In other words, minimally invasive governmental regulations, mostly leaving the free market untouched and manifesting growth paradigms, are unfit for current challenges.

In this line of reasoning, all three measures of the CAP can be interpreted as varieties of a market fix as described in Mazzucato and Ryan-Collins (2022). In this view, the government (or the European Union (EU) in this case) only has the responsibility to abolish market failures, and then the *invisible hand* efficiently allocates resources and enables new economic pathways to growth (Blandford 2010). So, the responsibility to transform agri-food systems lays with primary producers, the industry and consumers, and not with governments or communities (Candel 2022). However, "markets are blind [...]. They may neglect societal and environmental concerns" (Mazzucato 2015, p. 62). Instead of following socially and economically desirable pathways, markets head in path-dependent directions. In addressing challenges such as environmental degradation or climate change, governments must lead not simply by fixing market failures but by actively regulating markets (Mazzucato 2016).

In another line of reasoning, it can be argued that the CAP is in fact going beyond traditional neoclassical policy-making.The European Green Deal aims to reach climate neutrality by 2050 and social justice together with growth decoupled from resource use (European Commission 2020a). Further, in recent CAP reforms, a shift away from the prevailing paradigm of agricultural intensification towards sustainable agriculture has been observed (Skrimizea et al. 2020). As such, regulatory measures that address non-market, environmental issues are implemented in policy-making. The 'greening' payments (which amounts to 30% of the income support and affects 70% of the farmland) reimburse farmers for protecting the environment and biodiversity, "since market prices do not reflect the work involved" (European Commission Directorate-General for Agriculture and Rural Development 2018, p. 7). In this sense, the CAP payments are already de-emphasising yield as the sole outcome of agricultural production.

Further, the CAP measures manipulate agricultural markets and thereby go beyond neoliberal theories. The CAP's subsidies can be seen as a form of liberal paternalism. Liberal paternalism, as coined by Thaler and Sunstein (2003), steers people in directions that promote their welfare, while preserving freedom of choice. Thaler and Sunstein argue that "a policy counts as paternalistic if it is selected with the goal of influencing the choices of affected parties in a way that will make those parties better off" (2003, p. 175). With the cross-compliance rules, CAP subsidies are tied to goals that should be/are in the long-term interest of farmers and society in general, promoting environmental, societal and economic welfare. However, farmers are free to not comply with the rules. In that sense, the CAP basic payment scheme is a liberal paternalistic tool, going beyond traditional neoclassical policy-making.

In the last part of this section, a philosophical thought experiment is developed. Transformations of the agri-food system are highly political and will create winners and losers (Herrero et al. 2020). While there are various practical approaches on how to navigate agri-food system transformations (e.g. in Duru et al. 2015; Herrero et al. 2020), here I want to propose a thought experiment – without actually conducting the thought experiment and coming to a conclusion – on how to approach design choices of agriculture 4.0. The thought experiment is inspired by the 20th century political philosopher John Rawls and based on his *veil of ignorance*. The *veil* is Rawls' tools to construct a just and fair political system. This *veil* creates an original position that removes the identities of each individual in that position. As such, the subjects within the original position are without gender or age, race or class, power or wealth. With the *veil of ignorance* neutral subjects are put on a white sheet of paper and asked to agree on rules that create a just and fair society. The neutral subjects are aware of general facts and common sense, such as scarcity of resources, natural human social interactions and general scientific knowledge. They just do not know which position they have within the societal fabric. From this original, neutral state, subjects are asked to agree on societal principles. In theory, when decision-makers are stripped off their self-interest, their designed society should be just and fair (Rawls 1971, 1993).

Agriculture 4.0 can also be theoretically designed with the concept of the *veil*. All actors within the food system are placed on the 'white sheet of paper' with a *veil of ignorance*. The actors are farmers and future primary producers, supply chain actors, consumers and financial institutions, representatives of various societal groups, especially marginalised groups, and the biodiversity, environment or nature as a personified actor. With the *veil of ignorance*, the actors are unaware of their role and position within the agri-food system. The actors know about technological possibilities, environmental and resource limitations, climate change challenges and demand increases. The *veil of ignorance* can function as a moral reasoning device and promote impartial decision-making. By removing potentially biasing information about who will be a loser or a winner of a policy, the greater good is promoted. In experimental ethics studies it has been found that decisions are more impartial and socially beneficial when taken behind the *veil* (Huang et al. 2019).

While the *veil* has been used as a tool in experiments, when it comes to designing sustainable agri-food systems, a practical application is difficult. But still, the concept can inspire future research and stakeholder discussions. Such a wide-scope thought experiment aims at normative statements, principles or theories (Pölzler and Paulo 2021). In the end, Rawls' goal of distributive justice is not far from the ideas of a economic, environmentally and socially responsible and balanced, intergenerational just distribution of (agricultural) goods. Without any self-interest, pre-determined goals and knowledge of existing structures, agri-food system actors with the *veil of ignorance* should be able to come up with a just and fair agricultural production system of the future.

6.3 Policy and Business Implications and Recommendations

6.3.1 Policy

This thesis provides several recommendations on how to shape innovation-friendly policies and to promote the uptake of sustainable innovations. In this section, I summarise the policy recommendations relating to i) microbial applications in general and ii) uptake of sustainable innovations and practices.

6

First, European policy makers can shape the research, development and adoption of microbial applications through authorisation, legislative measures and research funding programmes, such as Horizon Europe. I go through each of these three actions, beginning with authorisation. For conventional chemical products, the application and approval process for a license to use new PPP is costly and lengthy, and can take more than a decade. For microbial applications – or microbial biological control agents – the authorisation is slow in the EU (Sundh and Eilenberg 2021). This impairs especially innovations by small producers that do not have the financial resources to sustain the costly R&D phase and numerous years of authorisation. According to Möhring et al. (2020), the authorisation process needs to be simplified e.g. by having only one EU license providing authority instead of multiple authorities.

Then there are two legislative measures that can be taken on the EU level. First, the EU needs to define microbial applications more clearly. To date, microbial applications are referred to as 'microbial plant biostimulants' in the Production Function Categories (PFCs) of biofertiliser products (Regulation (EC) No 2019 / 1009). According to the same European Commission (EC) Regulation, biostimulants do not provide nutrients, but stimulate plants' natural nutrition processes and are 'fertilising products'.[1] The EC Regulation further states that "products aim[ed] solely at improving the plants' nutrient use efficiency, tolerance to abiotic stress, quality traits or increasing the availability of confined nutrients in the soil or rhizosphere, they are by nature more similar to fertilising products than to most categories of plant protection products." (Regulation (EC) No 2019 / 1009, preamble point 22). In other words, if microbial applications only target nutrient processes, their use and authorisation would fall under the EC fertiliser regulations. However, microbial applications are also set out to substitute PPP. In the EC's regulation on PPP, the use of micro-organisms (note the change of wording)[2] is regulated when they have general or specific active substances against harmful organisms on (or parts of) the plant (Regulation (EC) No 1107 / 2009 Article 2, 2). Two things can be observed from this: i) terms are used inconsistently and interchangeably (biofertilisers and biostimulants, biocontrol agents, micro-organisms and microbial stimulants), ii) microbial applications, defined as a combination of a biopesticide and a biofertiliser, are not covered by EU legislation, yet. Consequently, first, a unified, clear terminology needs to be developed, and second, legislation for microbial applications exhibiting fertilising and PPP characteristics needs to be drafted. Only if the legal framework is clear, authorisation of microbial application products can be guaranteed, and microbial application technologies are developed and adopted.

Second, the EU can restrict the use of conventional fertilisers and PPP and thereby stimulate the uptake of alternative products. Following the EC Directive on Sustainable Use of Pesticides (2009 / 128 / EC), fewer chemical pesticides will be allowed in the EU, and controversial chemical substances will disappear from the product portfolios of suppliers (Robin and Marchand 2019). Yet, to date, some of these controversial substances, the herbicide Glyphosate for instance, have received an extension of approval (European Commission 2022). The Sustainable Use of Pesticide Directive (SUD) was designed to reduce the risk and impact of pesticides on human health and

[1] "*fertilising product* means a substance, mixture, micro-organism or any other material, applied or intended to be applied on plants or their rhizosphere or on mushrooms or their mycosphere, or intended to constitute the rhizosphere or mycosphere, either on its own or mixed with another material, for the purpose of providing the plants or mushrooms with nutrient or improving their nutrition efficiency" (Regulation (EU) No 2019 / 1009 of the European Parliament and of the Council of June 5, 2019, point 1 of Article 2).

[2] "*micro-organisms* means any microbiological entity, including lower fungi and viruses, cellular or non-cellular, capable of replication or of transferring genetic material" (Regulation (EC) No 1107 / 2009 of the European Parliament and of the Council of October 21, 2009 Article 3, 15)

the environment, for instance by promoting the use of non-chemical alternatives to PPP. To date, the SUD is only moderately effective in achieving this objective (Karamfilova 2022). Only if the SUD is more strictly enforced through actions of the Member States, farmers will feel the need to switch to alternative PPP. Only then, the development, diffusion and adoption of such alternatives is fuelled.

The EU can further shape microbial application development, diffusion and adoption through research funding. Research interest in microbial applications for agricultural purposes has increased in the last years and remains a topic of interest (Elnahal et al. 2022). In the latest Horizon Europe call, which opened in December 2022, the EC's main funding programme for (Research and) Innovation Actions, there are three proposal calls directly related to the use of microbes in the food system alone. This marks the growing political relevance assigned to microbial applications as alternative PPP and fertilising products. Political support and funding of research projects can fuel the efficiency enhancement of microbial applications.

Second, throughout this thesis, I touch upon several ways on how to influence the uptake of sustainable innovations. From this, several policy recommendations can be derived. For instance, in this thesis, the importance of understanding farmer behaviour to design effective interventions is stressed, which is also crucial in agricultural policy design (Pannell and Claassen 2020). For this, behavioural and experimental economics provide a valuable toolbox (Lefebvre et al. 2021). The toolbox contains various *ex ante* and *ex post* analysis tools (Thoyer and Préget 2019), such as hypothetical choice experiments (Latacz-Lohmann and Breustedt 2019), lab-in-the-field experiments (Thomas et al. 2019) and Randomised Control Trials (RCTs) (Behaghel et al. 2019). The toolbox should be used throughout the EU policy cycle, not least *ex ante*, i.e. in the preparation of and all the way to the implementation of policies and their impact assessment. The EU Competence Centre on Behavioural Insights implements such *ex ante* and *ex post* behavioural analyses of the CAP (e.g. Dessart et al. 2021, 2019; Dessart 2019; Espinosa-Goded et al. 2010). The implementation of evidence-based policies is then up to policy makers.

Further, in this thesis, the importance of extension services and knowledge provision for the uptake of sustainable innovations is stressed (Chapters 2, 3 and 4). The exposure to scientific knowledge and learning from science provides pathways towards the increased use of sustainable innovations (Montpetit and Lachapelle 2015). Extension services play an important role in providing information to farmers. The EU, as an innovation market enabler, has the important role to finance and support such extension services (Chapter 6). Extension services need to adapt to the changing demands of farmers and society, and increasingly make use of information technology-based tools

(Norton and Alwang 2020). Informational videos on novel technologies are an example of new pathways for extension (Chapter 4). Extension services need to train staff adequately, remain up-to-date and gain the trust of farmers, an important prerequisite for technology adoption (Chapter 3).

6.3.2 Business

Back in 2009, Berg noted an increased popularity of microbial applications due to improved efficacy and consistency. The authors predicted an annual growth rate of 10% world wide. In the EU, between 2011 and 2017, biocontrol agents constituted 50% of the new applications for approvals of active substances and the market for biocontrol agents is predicted to grow annually by 11% between 2020 and 2025 (Council of the European Union 2022). The industry is expecting a higher demand for biopesticides due to increasing demands for organic and sustainable foods, as reported by the EU Council (before the rise of inflation levels) (Council of the European Union 2022). Turning to biofertilisers, the global market was growing annually by 10% to 14% with a size of USD 1.327 billion in 2018, of which the largest share is attributed to nitrogen fixing products, according to commercial market research agencies in 2021.

In this thesis, I provide insights on how to stimulate the adoption of microbial applications, given that the efficacy of microbial applications is enhanced. These insights are condensed here as business recommendations. In addition, implications and recommendations for farmers are provided.

For microbial application developers, a transition from the lab to farm applications needs early attention in the development process to ensure that microbial applications realise their potential in a global sustainable agriculture (Parnell et al. 2016). First and foremost, microbial application developers, which includes businesses and researchers, should focus further on enhancing the efficacy of microbial applications in terms of PPP and fertiliser reduction, and disease alleviation potential (Chapter 5). Second, in the course of scaling up the production, prices need to be reduced (Chapter 5). The following recommendations are conditional on these prerequisites.

In the transition from the lab to the field, outreach campaigns that inform farmers on the long-term benefits are crucial to facilitate and promote the adoption of microbial applications (Mitter et al. 2021). Potentially, farmers do not understand how microbial applications work, which raises their scepticism. The results in Chapter 4 illustrate that providing an informational video can be an effective way to promote the uptake of microbial applications. The results of Chapter 3 show that trust in the safety and efficacy of microbial applications is important, too. Trust can be created through long-term field trials, showing the efficacy of the products. Information on the technical and practical aspects need to be provided from trustworthy sources (Timmusk et al. 2017). In addition, different stakeholders should be involved in the development and diffusion of microbial applications. Through communities of practice and peer-to-peer exchange, enhanced by extension services and technology providers, new, sustainable norms can be created (Chapter 3).

Innovation adoption needs to be accompanied by learning. As such, microbial application providers should offer training and advice for first-time adopters. Other marketing tools, such as a free soil tests and advice on farming practices as well as informational videos can stimulate uptake (Chapter 4). As demonstrated in this thesis, farmers are generally risk-averse, which impairs innovation adoption (Chapter 4). Providers need to creatively come up with risk reducing tools to motivate the uptake of microbial applications. For instance, contracting agreements can be a solution especially for small farms with limited access to capital (Wang et al. 2022).

Considering that there are more microorganisms in a spoon of soil than there are humans on planet earth (Kendzior et al. 2022), the effectiveness of applying additional microorganisms in open fields might always be limited. As a suggestion for gathering further knowledge, microbial application producers can first investigate the use of microbial applications in indoor systems, such as vertical farms. Usually, vertical farming systems use media in an hydroponic or aquaponic system (van Delden et al. 2021). In these smaller scale and more controlled systems, the use of microbial applications can be more promising at first than in open fields. Further, price premiums of vertically farmed products are higher than of arable products, which leaves room for experimenting with more expensive PPP and fertiliser substitutes. Thereby, knowledge on how microbial applications function is enhanced. This can be used to further develop microbial applications to make them fit for the use in open fields.

Conventional PPP and fertiliser producers will become increasingly subjected to product bans and restrictions. Therefore, farmers will search for alternatives to provide the necessary products for agricultural production (Berg 2009). This is a promising market niche for producers. Microbial application producers should consider collaborations and joint ventures with other suppliers, such as smart farming technology providers.

For farmers, the advice is to partially adopt microbial applications on the farm to test their effectiveness in the given environment. Effectiveness is soil- and climate-dependent. Often, adoption is seen as a binary choice (adoption yes/no), while in fact, the farm-level adoption rate is a continuous variable (Pannell and Claassen 2020). As such, farmers can decide to try out microbial applications on parts of their fields on just one or two crops in one season and experiment, based on advice by extension services and technology providers, without taking excessive risks. Yet, microbial applications are expected to only demonstrate their full potential in the long term. The adoption of microbial applications requires a long-term commitment, whereas the benefits are not directly visible. Therefore, partial adoption of microbial applications should fit within the cropping plan, taking crop rotations into account. It is important that adopting farmers then reach out to peers, demonstrate their results and provide practical advice (Chapter 3).

Farmers can benefit from the adoption of microbial applications by a reduced PPP and fertiliser use and improved environmental footprint (Chapter 5). Further, consumers are willing to pay a price premium for more sustainable and healthier products (Ali et al. 2021).

6.4 Reflections on Materials and Methods

Hypothetical vs. Actual Behaviour. In Chapter 3 and 4 of this thesis, hypothetical behaviour is investigated. There is always the risk that stated preferences and intended behaviour do not materialise into revealed preferences and actual behaviour. It is a clear limitation of Chapter 4 whether the informational video indeed leads to an increased actual uptake of microbial applications. Further, it is a clear limitation of Chapter 3 that we could not observe farmers' drivers and barriers directly from their behaviour. However, in the case of a non-marketed product, such as microbial applications, it is not possible to investigate actual behaviour of farmers. To investigate actual uptake of microbial applications, the product would need to be more widely available to and known by farmers. In upcoming Horizon Europe Innovation Actions, the behaviour-intention gap can be reduced. The behavioural gap between stated and actual behaviour is a well-known problem, but *ex ante* assessments are critical (Möhring et al. 2022). Only with such *ex ante* assessments, external and institutional factors that impair adoption can be identified (Quevedo Cascante et al. 2022).

Composite Indicators. In Chapter 2 and 5, I use composite indicators to measure complex constructs. In Chapter 2, I measure innovativeness with an innovation index. In a similar way, in Chapter 5, I measure sustainability with an index. Composite indicators support interpretation, communication and comparison (Saisana et al. 2005). It makes sense to use composite indices when the aggregated index contains more information than its parts. In both chapters, this is the case. In Chapter 2, we describe why a single proxy does not reflect innovation systems adequately. When it comes to sustainability, by definition, a three pillar concept cannot be measured with a single indicator. The benefit of composite indicators is that they can display the trade-offs within complex, wicked systems. Indicators are useful for comparison and to make a 'point for action', but to benchmark decision-makers, guide decision-making, single variables and quantitative analyses are more informative (Saltelli 2007).

Both indices used in this thesis suffer from data limitations. In Chapter 5, the selection of single indicators has been dictated by data availability. Yet, a participatory or theory-based approach should rather have been used to select single indicators. Generally, the range of available farm-level data limit sustainability indicator assessments (Latruffe et al. 2016). The selection of indicators is difficult and experts even disagree in the choice of selection criteria for sustainability indicators (de Olde et al. 2017). In line with the majority of studies, in Chapter 5, economic viability indicators are used to measure the economic pillar of sustainability. Environmental impact indicators are used assuming a cause-and-effect relationship between PPP and fertiliser use and environmental impact. With respect to the social pillar, only the farm community level could be assessed, disregarding society as a whole. The social pillar of sustainability is generally difficult to measure. It gets and even more difficult when assessing agriculture's role in society, such as designing landscapes and maintaining the quality of life in rural areas (Latruffe et al. 2016). Data limitations and measurement problems are enhanced in the case of *ex ante* innovation evaluations.

According to Latruffe et al. (2016) and de Olde et al. (2017), the sustainability indicators should be selected by stakeholders. Indicator selection affects the outcomes of sustainability analyses. When conducted for policy evaluation, these analyses affect stakeholders, such as farmers. Therefore, the selection of indicators should be a process in which affected stakeholders are involved. This can create relevant and context-specific assessments to improve sustainability performance and trigger the orientation and actions of participants towards more environmentally friendly outcomes (de Olde et al. 2017).

To aggregate and weight the single indicators, we use the BoD approach (Cherchye et al. 2006). The BoD approach overcomes the problem of subjective aggregation choices (Mergoni et al. 2022) and integrates aggregation, weighting and index construction (Gan et al. 2017). The resulting index depicts each observation in the best possible light relative to the other observations (Mergoni and De Witte 2021). As such, the BoD approach is the right choice because the researchers observed the relative position of each farm given their innovation or sustainability choices. In this thesis, no subjective judgement on the weighting of sustainability indicators or single innovation proxies is done. So, the necessary trade-offs, as discussed in the introduction, are transparent.

However, as discussed in Section 6.1.3, this approach yields a relative, comparative measure of sustainability. Depending on the goals of the analysis (descriptive vs. normative), the weights need to be endogenously or exogenously defined. Instead of setting weight bounds based on expert information, a theory-guided approach could be taken.

Data, Collection and Gaps. Data collection among farmers is becoming increasingly difficult. In this thesis, low response rates could have been caused by the timing of the data collection, the length of the survey (Chapter 3 and 4) and the absence of a financial compensation (Chapter 3). This has also been observed in other research projects (Pennings et al. 2002). Another reasons for an increasing fatigue to participate in (online) studies could be the increasing number of requests by researchers and governmental institutions. Further, farmers do not always see the practical implications of the research for their farm. This has been especially experienced during the data collection for Chapter 4 and for the contribution to Rommel et al. (2022b). Additionally, farmers' workload and administrative burdens are increasing and they are hesitant to commit to time-intensive data collection that they do not directly benefit from. Consequently, the length, timing, sender and form and amount of payment are important barriers to take into account when designing farmer surveys or experiments (Baaken et al. *forthcoming*).

In Chapter 2, I use FADN and Dutch Innovation Monitor data to investigate farmers' innovativeness and efficiency. Regarding the Innovation Monitor, I advise to adjust the survey and increase the number of farmers surveyed. In specific, an expert-approved multiple choice list of technologies should be added. A qualitative description of technologies can be optionally provided in case the technology is not part of the list. This extension does not only simplify the data collection process and makes it quicker for farmers to fill in but also improves the quality of data and their analysis. Further, ideally, all FADN farmers should be included in the sample of the Innovation Monitor. In order to facilitate evidence-based policy-making, a solid data base is crucial.

The FADN contains only few data on sustainability. Yet, a broader set of indicators is needed to authentically assess farm sustainability; not least for this reason, there have been calls for an extension of the FADN towards a Farm Sustainability Data Network (FSDN) (Kelly et al. 2018; Uthes et al. 2020). According to Vrolijk and Poppe (2021), in an FSDN, data quality, the availability of long time series and a minimal burden for farmers need to be balanced. The authors find that the additional sustainability data would increase the costs of FADN data collection by 40%. However, smart farming and other digital technologies are expected to simplify data collection, increase the accuracy of data and decrease the burden on farmers.

In an optimal approach to data collection farmers are compensated for their participation. The compensation should be oriented to the opportunity costs of farmers, which depend on the country and farm system. Beyond compensation, farmers should benefit from their participation, either by gaining insights or advise on their own farm operation or by having a sense of contributing to research that might affect them at some point. Both is very costly and the benefits of evidence-based policy-making should outweigh the costs of data collection. This also holds for possible extensions of the FADN into FSDN and of the Innovation Monitor.

Expert Elicitation. Expert elicitation is one way to fill data gaps and to explore innovations *ex ante*. In this thesis, I use a simple expert elicitation approach in Chapter 2 and a more complex Delphi approach in Chapter 5. In Chapter 2, I use an existing expert survey, which I adjust to the Dutch arable farming context. The benefit of using a pre-existing survey is that the questions are validated and pre-tested. The survey was sent to a number of experts directly via e-mail as a pdf form. The experts were mostly Dutch and even though the survey was in English, experts had the option to reply in Dutch to the open questions. We contacted twelve experts and got a full and valid reply from eleven of them. The experience was generally very positive. In Chapter 5, I use the more complex Delphi method to elicit expert information. In Chapter 5, in the context of sustainability of microbial applications, the problem and question is less clear and defined. Therefore, the Delphi approach, starting off with a participatory workshop, was conducted. For instance, in the first elicitation round, different scenarios were investigated. Yet, it turned out that the experts evaluate the effectiveness of microbial applications in different scenarios similarly. Therefore, the expert elicitation was adjusted in subsequent rounds. In such less defined contexts, a flexible Delphi approach is helpful with the aim to reach a certain level of agreement.

The Delphi method has been a well-accepted and popular method for over half a century (Linstone and Turoff 2011). It helps to anticipate future events and has been used in numerous agricultural studies before. For example, Jones et al. (2017) investigated the agro-economic benefits of certain genetically modified crops for farmers and consumers. Torgerson et al. (2021) applied the Delphi method to explore to what extent the by-products of insect production could be used as a crop and soil health promoter. Gardner et al. (2021) identified novel crops for south-west England with a Delphi method and showed that the assessment of an expert panel can be used in crop suitability models. In this thesis, the Delphi method is used to collect expert estimates on microbial applications as no information or data are readily available. Against the common misconception that the goal of the Delphi method is ultimate consensus, "[t]he value of the Delphi is [...] in alerting the participants to the complexity of issues, by forcing, cajoling, urging, luring them to think, by having them challenge their assumptions" (Coates 1975, p. 194, as cited in Linstone and Turoff (2011)). We achieved this through the workshop and consecutive expert elicitation surveys. However, the Delphi method also has its downsides, to be found mainly in its lengthy process. As such, several experts got lost on the way. Compared to the simple, one-time expert elicitation, fewer experts replied to the Delphi survey, despite their involvement in the same research project. Yet, this could also be related to the fact that the Delphi method has been applied in a less defined context.

Simulation Modelling. Another way to circumvent data limitations are simulation models, as conducted in Chapter 5. Monte Carlo simulations are stochastic models that can take into account the impacts of uncertainty and variability. Multiple probability simulations turn model inputs into model outputs. Each model input is defined by the parameters in its probability distributions (Gebrezgabher et al. 2012). However, every model is only as good as its input data. For instance, we observed that the input prices and dosages by the experts are different from industry prices and dosages. Given correct ranges of data, *ex ante* modelling exercises are useful for information provision and impact assessment (Möhring et al. 2022).

6.5 Future Research

In each of the four research chapters, recommendations for future research are provided. In this section, these recommendations are compiled and extended. The recommendations concern future research on microbial applications, the uptake of sustainable innovations and the innovation index.

First and foremost, research on microbial applications needs to enhance their efficacy in alleviating abiotic stresses and diseases, and reduce effect uncertainty and context-variability. To date, little is known on how microbial applications bio-physically affect plant growth and resilience. This foundational knowledge needs to be established as a baseline (Chapter 5). Further, the long-term effects of using microbial applications need to be investigated and quantified. This also includes potential negative, spillover effects on the landscape level.

This bio-agronomic research on microbial applications needs to be accessible to researchers in other fields. As such, it is crucial that data on the effects of microbial applications can be **f**ound, are openly **a**ccessible, **i**nteroperable and **r**eusable (FAIR). Based on these data and insights, life cycle analyses along the entire supply chain can be conducted. The MC model developed in Chapter 5 can be used as a starting point, which can be extended and updated with more real-life data. In future research, the system boundary should be widened and the large-scale production of microbial applications compared to fertiliser and PPP production (Chapter 5). In addition, bio-economic modelling approaches that integrate the bio-physical effects of microbial application in crop models can precisely quantify their environmental and economic effects as soon as the bio-physical pathways of microbial applications are known (Chapter 5). Such models can be extended by assumptions about other technology adoptions, such as smart farming technologies (Chapter 6), or forward-looking models of climate change or salt stress (Chapter 5). On the industry level, production scale-up needs to be investigated alongside pathways to lower the production costs of microbial applications.

Second, in this thesis, a number of intervention strategies to stimulate the uptake of microbial applications are proposed. In future research, the suggested intervention strategies from Chapter 3 and 4 can be tested as to see whether they indeed increase the actual uptake of microbial applications (or any other similar sustainable innovation). For instance, RCTs can be an effective tool to test the effectiveness of interventions (Chapter 3). In future research, the effectiveness of informational videos to stimulate *actual* innovation uptake should be investigated together with the 'stickiness' of the intervention. The persistence of the effect of the informational video should be tested and compared with other types of incentives and/or in combination with nudges (Chapter 4). Moreover, it should be tested whether video interventions are effective, independent of the context and the technology (Chapter 6).

Further, in this thesis, a number of drivers and barriers for innovation adoption are identified. Apart from the well-researched influence of risk and probability distortions (Chapter 4), the influence of capability, opportunity and motivation are identified (Chapter 3). It is recommended that these identified drivers and barriers are verified, adjusted or complemented in stakeholder discussions (Chapter 3). Another way to verify the results from Chapter 3 is to replicate the study with a larger sample, potentially using face-to-face interviews.

Third, with respect to the innovation index, it is recommended to also include a single indicator on knowledge generation. This can be proxied for instance by time spend in trainings. Further, innovation efficiency, i.e. the ratio between innovation inputs and outputs, can be investigated (Chapter 2). In Chapter 2, an extension of the Innovation Monitor and its data collection is also discussed.

Last, in this thesis, the focus is on arable farmers in the Netherlands and Germany, focusing on wheat and potato crops. However, Microbial applications affect different crops in different environments differently. Thus, the findings in Chapter 3 to 5 could be different in an another farming system, another crop or in other countries. For instance, microbial applications could have a larger impact on the sustainability of crops with greater profit margins (Chapter 5). Similarly, while the improvements that can be reached with microbial applications are limited here, there might be a larger potential on other crops and/or in developing parts of the world. All in all, the findings on the sustainability effects of microbial applications cannot be directly transferred to other fields and contexts. The findings on behavioural drivers and barriers and on stimulating uptake of microbial applications can be used as a starting point (Chapter 3 and 4). Yet, in other cultural contexts and environments the behavioural drivers and barriers and the effect of certain interventions might be different. This is subject to further research.

6.6 Main Conclusions

- There is no relationship between farmers' innovativeness and farm efficiency, and there is also no time trend. (Chapter 2)
- There is a positive correlation between the Capability, Opportunity, Motivation - Behaviour (COM-B) elements of the Behaviour Change Wheel (BCW) and farmers' likelihood to adopt microbial applications. (Chapter 3)
- Trust in microbial applications is an important driver, and lack of knowledge and professional support are barriers for the adoption of microbial applications. (Chapter 3)
- Three intervention strategies to stimulate the uptake of microbial applications are i) norm creation and enablement, ii) education and learning, and iii) building trust by providing incentives. (Chapter 3)
- Large-scale and long-term field studies are needed to motivate on-farm microbial application adoption. (Chapter 3)
- Informational videos can stimulate farmers' intention to adopt microbial applications. (Chapter 4)
- Farmers' risk aversion reduces their willingness to adopt microbial applications. (Chapter 4)
- Extension services, advisers, and knowledge and learning play an important role in the uptake of sustainable innovations and in translating innovation benefits to farm (economic) benefits. (Chapters 2, 3 and 4)
- Farmers expect advisers to acquire up-to-date knowledge, to enable dissemination and provide clear advice. (Chapter 3)
- Microbial applications are sustainable, but are not (yet) able to enhance the sustainability of Dutch potato production. (Chapter 5)
- The benefits of microbial applications are not enough to compensate for the high uncertainty in their efficacy and the high prices. (Chapter 5)
- In a potato production system with microbial applications, it is expected that 60% less CO_2 and 6.6% fewer active substances are emitted, compared to a conventional potato production system. Microbial applications are expected to increase yield by 3.7%. (Chapter 5)

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Summary

Against the backdrop of environmental degradation, climate change, population pressure and supply chain disruptions, the need for sustainable farming becomes more apparent. Agricultural innovations support the transition towards sustainable agri-food systems. Microbial applications are an example of such a potentially sustainable innovation. Microbial applications serve as an environmentally friendly supplement or substitute for plant protection products and fertilisers by alleviating abiotic stresses, strengthening crop resilience and supporting plant growth and quality. As agronomists and plant scientists continue to improve microbial applications' effectiveness, this thesis looks at microbial applications from a social science perspective. The objective of this research is to investigate sustainable innovations in general and microbial applications as an example from a farmers' perspective.

In Chapter 2, the relationship between farmers' innovativeness and farm technical efficiency is assessed. Innovativeness, that is, how innovative a farmer is, is measured with an innovation index. The index is an expert-weighted Benefit-of-the-Doubt composite of technology adoption, development and initiation, investment and continuity. With the use of a composite index, the entire innovation process, in the sense of complex Agricultural Innovation Systems (AIS), is described. Thereby, the index goes beyond a one-dimensional innovation proxy that is tied to a specific innovation. The innovation index is adapted to Dutch arable farms, but could be adapted to other countries and farming systems. A longitudinal representative Farm Accountancy Data Network (FADN) sample of Dutch arable farms is investigated. The empirical findings reveal that innovativeness and efficiency are not related. The pre-registered hypothesis that the relationship between innovativeness and efficiency is inverted U-shaped is rejected. Further, a change over time cannot be observed and the hypothesis that innovation front-runners become more efficient is rejected. There are two potential explanations for these findings. First, knowledge and capital enhancements that go along with the innovation process could be heterogeneous and explain

different effects on efficiency. Second, a lack of socio-political support could impair the translation of innovativeness into efficiency gains.

In Chapter 3, the behavioural drivers and barriers associated with the likelihood to adopt microbial applications are investigated and interventions recommended. Translating behavioural drivers and barriers into effective interventions can foster the uptake of sustainable innovations and farming practices in general and of microbial applications in specific. Successfully promoting the uptake of such sustainable innovations eventually allows achieving Farm to Fork targets and improving food security. The Behavioural Change Wheel (BCW) and its capability, opportunity, motivation-behaviour (COM-B) model are employed. Data are collected via a semi-quantitative online survey among 196 Dutch and German arable farmers. Trust in microbial applications is found to be an important driver. Results also suggest lack of knowledge and professional support as important barriers for the adoption of microbial applications. Based on the identified drivers and barriers, three interventions are recommended: i) norm creation and enablement, ii) education and learning, and iii) trust building by providing incentives. The acceptance and success of a behavioural intervention depends on the choice of the interventionist. For instance, the role of governmental institutions in enforcing the adoption of microbial applications is perceived as problematic by farmers. Instead, farmers expect advisers and farmer organisations to become active in knowledge transmission and field studies. While the BCW provides a comprehensive framework to connect behavioural factors and interventions, several shortcomings of the methodology are observed as well. The BCW and its COM-B model require a fine-grained, labour- and resource-intensive process, which is difficult to execute in practice and to apply in semi-quantitative online surveys.

In Chapter 4, the effect of farmers' risk aversion and the stimulating impact of an informational video on farmers' intention to adopt microbial applications is assessed. Risk-averse farmers are often reluctant to adopt such innovations. An online survey containing an experiment and a monetarily incentivised Multiple Price List (MPL) lottery game is conducted among 98 Dutch arable farmers. In the experimental part, a treatment group watched the informational video while the control group received no information. I test whether the treatment group that watched the video is more likely to adopt microbial applications compared to the control group. In the lottery part, both groups played a randomised order of lotteries to elicit the subjects' risk attitudes. The analysis leads to two main findings. First, the video has a significant effect on the farmers' intention to use microbial applications in primary production. Informational videos can be an effective, low-cost tool to stimulate the adoption of innovations such as microbial applications. Second, the results suggest that the intention to use microbial applications is likely influenced by the subjects' risk attitude.

In Chapter 5, the capacity of microbial applications to enhance the sustainability, including environmental, economic and social dimensions, of Dutch potato production is assessed. A baseline scenario and a microbial application scenario are modelled with Monte Carlo simulation. The scenarios are compared by means of a composite sustainability index. The microbial application scenario is based on data from a Delphi expert elicitation. The results show that microbial applications are sustainable. The effect of microbial applications on environmental sustainability is likely positive, indicated by almost 60% lower CO_2 emissions and 6.6% fewer active substances. Additionally, microbial applications are expected to increase yield by 3.7%. However, the results suggest that microbial applications are not able to enhance the sustainability of the Dutch potato production system due to three main disadvantages: their high costs, their effect uncertainty and their inability to prevent potato diseases. Overall, the modelled baseline scenario is significantly more sustainable than the microbial application scenario. Technological advancements are required to further reduce the costs per unit of production. The results of this study contribute to an understanding of the implicit uncertainty of microbial application effects. Although effect uncertainty is mentioned in other studies, we explicitly quantify it as a core element in our model.

The two main contributions of this thesis, as a collection of four Chapters and a General Introduction and Discussion, are insights into microbial applications and methodological considerations. First, this thesis provides insights into the uptake factors and sustainability effects of microbial applications. The research informs microbial application producers and developers on how to improve the products and offers recommendations to suppliers, advisers and policy makers on how to stimulate adoption. Second, the main methodological contribution of the research chapters concerns the conceptualisation of innovativeness in AIS by using composite indicators. This thesis also exemplifies *ex ante* innovation research, investigating adoption and effects of an innovation before its market uptake. *Ex ante* assessments steer holistic evaluations and provide prior information on uptake and effects to stakeholders.

Main Conclusions

- There is no relationship between farmers' innovativeness and farm efficiency, and there is also no time trend. (Chapter 2)
- There is a positive correlation between the Capability, Opportunity, Motivation - Behaviour (COM-B) elements of the Behaviour Change Wheel (BCW) and farmers' likelihood to adopt microbial applications. (Chapter 3)
- Trust in microbial applications is an important driver, and lack of knowledge and professional support are barriers for the adoption of microbial applications. (Chapter 3)
- Three intervention strategies to stimulate the uptake of microbial applications are i) norm creation and enablement, ii) education and learning, and iii) building trust by providing incentives. (Chapter 3)
- Large-scale and long-term field studies are needed to motivate on-farm microbial application adoption. (Chapter 3)
- Informational videos can stimulate farmers' intention to adopt microbial applications. (Chapter 4)
- Farmers' risk aversion reduces their willingness to adopt microbial applications. (Chapter 4)
- Extension services, advisers, and knowledge and learning play an important role in the uptake of sustainable innovations and in translating innovation benefits to farm (economic) benefits. (Chapters 2, 3 and 4)
- Farmers expect advisers to acquire up-to-date knowledge, to enable dissemination and provide clear advice. (Chapter 3)
- Microbial applications are sustainable, but are not (yet) able to enhance the sustainability of Dutch potato production. (Chapter 5)
- The benefits of microbial applications are not enough to compensate for the high uncertainty in their efficacy and the high prices. (Chapter 5)
- In a potato production system with microbial applications, it is expected that 60% less CO_2 and 6.6% fewer active substances are emitted, compared to a conventional potato production system. Microbial applications are expected to increase yield by 3.7%. (Chapter 5)

Index

About the Author

Annika Francesca Tensi, née Kloos, was born on October 14, 1992 in Bonn and grew up in the Rheinland between Cologne and Bonn. For her studies, she moved to the Netherlands in early 2013. She did her Bachelors at the University College Maastricht in Liberal Arts and Sciences, an interdisciplinary programme. She focused on Business, Economics and Sustainability, and graduated in February 2016 with a BA thesis entitled "Vertical Farming in the City: Sustainable food production in the sky or the hell on earth?". Afterwards, she moved to Wageningen to pursue her MSc in Management, Economics and Consumer studies at Wageningen University & Research (WUR). She followed the Business Economics track and graduated in spring 2019 with an MSc thesis entitled "The economic *success* recipe of craft beer brewers: An analysis of the definition of success and associated business strategies of European craft beer brewers". She did internships at Bayer Crop Science Germany, the German Sustainability Council (*Rat für Nachhaltige Entwicklung*) and the Food and Agricultural Organisation (FAO).

After her Masters, she stayed at WUR's Business Economics Group (BEC) to acquire her PhD, starting in spring 2019. The PhD project was part of the 'Sustainable Innovation of Microbiome Applications in the Food System' (SIMBA) project. The SIMBA project, an interdisciplinary EU Horizon 2020 project, aimed at providing innovative microbiome solutions to increase food security and nutrition.

Annika is one of the founding members of the Open Science Community Wageningen (OSC-W), founded in 2022. She also contributed to studies connected to the 'Research network on Economic Experiments for the Common Agricultural Policy' (REECAP). Generally, she is interested in sustainable agriculture, innovations and transitions. She employs methods from behavioural and production economics. She likes to crunch data and to analyse complex relationships, to engage with stakeholders and to work in close-knit, interdisciplinary and intercultural teams. In her free-time, you find her outdoors, running, hiking or cycling, or indoors being screamed at by her spinning instructor or in a quite corner enchained by a good read.

List of Publications

Published Peer Reviewed Articles

Tensi, A. F., Ang, F., & van der Fels-Klerx, H. J. (2022). Behavioural drivers and barriers for adopting microbial applications in arable farms: Evidence from the Netherlands and Germany. *Technological Forecasting and Social Change, 182*, 121825. (Chapter 3)

Rommel, J., Sagebiel, J., Baaken, M. C., Barreiro-Hurlé, J., Bougherara, D., Cembalo, L., ... & Zagórska, K. (2022). Farmers' risk preferences in 11 European farming systems: A multi-country replication of Bocquého et al.(2014). *Applied Economic Perspectives and Policy*.

Tensi, A.F., Ang, F. (2023). Stimulating risk-averse farmers to adopt microbial applications. *Q Open*. (Chapter 4)

___ under review

Tensi, A.F., Ang, F., van der Fels-Klerx, H. J. (2022). Microbial Applications and Agricultural Sustainability: A Simulation Analysis of Dutch Potato Farms. *Agricultural Systems*. (Chapter 5)

Slijper, T., Tensi, A. F., Ang, F., Ali B. M., van der Fels-Klerx, H.J. (2022). Investigating the relationship between knowledge and the adoption of sustainable agricultural practices: The case of Dutch arable farmers. *Journal of Cleaner Production*.

___ submitted

Tensi, A.F., van der Fels-Klerx, H. J. & Ang, F. (2023). Innovativeness and Technical Efficiency: Evidence from the Dutch Arable Sector. *European Review of Agricultural Economics*. (Chapter 2)

Annika Francesca Tensi
Wageningen School of Social Sciences (WASS)
Completed Training and Supervision Plan

Wageningen School of Social Sciences

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
A1 Managing a research project			
WASS Introduction Course	WASS	2019	1
'Nudging Farmers to Adopt Microbial Applications in Times of COVID-19' (best PhD presentation award)	AES Conference, online	2021	1
'Innovation and Rational Inefficiency: A DEA and Innovation Index Approach'	EAAE Congress, online	2021	1
'Farm innovation and technical efficiency of Dutch arable farms: An innovation index and DEA approach'	AES Conference, Leuven	2022	1
SIMBA project consortia meetings			
Organisation	SIMBA, Wageningen	2019	1
Attendance	SIMBA, online	2020	0.5
Attendance & presentation	SIMBA, online	2021	1
Attendance	SIMBA, hybrid	2022	0.5
Attendance & workshop	SIMBA, Spain	2022	1
Scientific Writing	Wageningen in'to Languages	2021	1.8
Following bi-weekly PhD content meetings	BEC, Wageningen/online		2
A2 Integrating research in the corresponding discipline			
Advanced Behavioural Economics	Utrecht University	2019	5
Experiments in Economics and Business	Utrecht University, online	2020	2.5
Mathematical Economics	University of Göttingen, online	2021	3
Efficiency and productivity analysis 2 – stochastic approaches	University of Göttingen, online	2021	3
Summer School: Experimetrics	University of East Anglia, online	2021	0.5
B) General research related competences			
B1 Placing research in a broader scientific context			
Crops, Physiology and Environment, HPP23806	WUR (Horticulture and Product Physiology)	2021	5
Statistical Uncertainty in Dynamic Models	PE&RC and WIMEK	2022	1.5
B2 Placing research in a societal context			
AES conference, workshop (organisation)	AES, online	2021	1
Entrepreneurship In- and Outside Science	CVC	2022	1.1

C) Career related competences/personal development			
C1 Employing transferable skills in different domains/careers			
Teaching/supervision: MSc thesis students	BEC	2021/2022	2
Competence Assessment	WGS	2019	0.3
Brain friendly working and writing	WGS	2019	0.3
Brain Training	WGS	2019	0.3
Introduction to LaTeX (online)	PE&RC	2020	0.3
Scientific Artwork – Vector graphics and images	WUR Library	2020	0.6
Council/Committee membership (4ECTS): Open Science Community		2021/2022/2023	4
Total			**42.2**

*One credit according to ECTS is on average equivalent to 28 hours of study load

Acknowledgements

As I pass the finish line of my personal *Grand Tour* that took four years, I am reminded that endurance and perseverance are key, but even more so, all the support that I received. Just like a rider in the *Tour de France*, I could not have made it alone.

Firstly, I would like to thank my *team manager*, Ine van der Fels-Klerx, and my *directeur sportif*, Frederic Ang. Ine, thanks for overseeing the sponsorship and general operation. Frederic, I could always rely on your ideas on efficient racing strategies and your Teams messages every time of the day – and night. It was not always encouraging to hear, but in the end you were right: *Gutta cavat lapidem, non vi, sed saepe cadendo*. Thank you both for following me in the support car and for coming up with a tactical plan trying to maximise my potential.

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an improvement of the common scientific practice, its conventions and rules. Thank you all for providing a great source of energy – the OSC-W *ride* was great fun!

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I would like to finish this thesis by taking a moment to acknowledge the privileges that have played a significant role in this achievement. Achievements are privilege-dependent and privileges are context-dependent. Being raised in an academic household and educated in one of the most prosperous countries in the European Union, I had access to incredible social security, human and financial support. These circumstances, along with the help of all the people mentioned in this section, have paved the way for this achievement. While these privileges were out of my control, I believe it's important to recognise them. As individuals, we should be conscious of our privileges and work towards removing barriers for those who are less fortunate in our communities, workplaces, countries, and the world.

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