Facilitating Precision Farming Adoption in Smallholder Agriculture

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Abstract

Small-scale farms are vital to Europe's food sovereignty, biodiversity, and ecological resilience. Yet, they are vanishing at an alarming rate. While industrialised agriculture has introduced certain efficiencies, it has also resulted in monocultures, the decline of rural communities, and widespread ecological degradation. Despite various policy efforts, smallholders continue to encounter increasing systemic pressures. This thesis explores the role of Precision Agriculture Technologies (PATs) in this context - not merely as tools for efficiency, but as potential enablers of smallholder autonomy, resilience, and sustainability. It evaluates both the benefits and the limitations of their adoption.

This research challenges the dominant techno-solutionist narrative, arguing that current implementations of PATs often reinforce the very structural inequalities they aim to address. These technologies tend to favour large agribusinesses, often putting farmers at a disadvantage by establishing new dependencies. By emphasising the gap between technological design and the everyday experiences of smallholders, the study reconsiders innovation as a social and systemic problem, rather than merely a technical one.

This thesis investigates how PATs can be reimagined to truly assist small-scale agriculture, drawing on thorough fieldwork and collaboration with farmers. The outcome is CropKit, a modular, open-source agricultural technology ecosystem tailored to meet the unique needs of smallholders. Central to this system is the CropKit Base, a lightweight and compact micro-tractor designed for flexibility and ease of use across various farming conditions. Functioning like a two-wheel tractor, the Base features three levels of autonomous control, allowing farmers to choose the most suitable interface for each task. Its functionality is further enhanced by a variety of modular attachments, which boost its adaptability. Collectively, these elements create a versatile system that integrates physical usability with digital insights, enabling gradual, accessible adoption while empowering farmers to remain autonomous stewards of their land.

Ultimately, this thesis calls for a radical rethinking of how agricultural technologies are conceived and implemented - not as top-down solutions, but as collaborative tools for systemic change. In the face of ecological crisis, it advocates for technologies that serve farmers, not the other way around, and places small-scale farms at the centre of a resilient and sustainable agricultural future.

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List of Abbreviations

AI	– Artificial Intelligence
BISS	– Basic Income Support for Sustainability
CAP	– Common Agricultural Policy
CNN	– Convolutional Neural Network
CIS	– Coupled Income Support
CIS-YF	– Complementary Income Support for Young Farmers
CRISS	– Complementary Redistributive Income Support for Sustainability
CSP	– CAP Strategic Plans
DSS	– Decision Support Systems
EAFRD	– European Agricultural Fund for Rural Development
EAGF	– European Agricultural Guarantee Fund
EIP-AGRI	– European Innovation Partnership for Agricultural Productivity and Sustainability
EPRS	– European Parliamentary Research Service
EU	– European Union
FAO	– Food and Agriculture Organisation
FMIS	– Farm Management Information Systems
GAECs	– Good Agricultural and Environmental Conditions
GDP	– Gross Domestic Product
HRI	– Human-Robot Interaction
IoT	– Internet of Things
ML	– Machine Learning
PA	– Precision Agriculture
PATs	– Precision Agriculture Technologies
PF	– Precision Farming
PSF	– Small Farmers Payment
PTO	– Power Take-Off
PTNs	– Plant Trait Networks
RDP	– Rural Development Programme
ROI	– Return on Investment
RTK	– Real-Time Kinematic
SDGs	– Sustainable Development Goals
SO	– Standard Output
TRL	– Technology Readiness Level
UAA	– Utilised Agricultural Area
UAV	– Unmanned Aerial Vehicle
UGVs	– Unmanned Ground Vehicles
USPs	– Unique Selling Propositions
VRA	– Variable Rate Application
VRT	– Variable Rate Technology

Chapter 1

Introduction

1.1. Context and Background

Every day, we consume food grown on farmland, yet we rarely consider its origins. Agriculture is not just an economic sector; it is the foundation of our food system and is deeply entangled with the escalating climate crisis. Across Europe, small-scale farms, which comprise the majority of agricultural enterprises, are disappearing at an alarming rate. Structural, economic, and climatic pressures are pushing them to the brink of survival. Yet, these farms are indispensable for biodiversity, ecological resilience, and sustainable food systems. Their decline is not just a shift toward large-scale agribusiness but a profound ecological and societal loss.

The rise of industrialised agriculture has led to homogenised landscapes, declining biodiversity, and a food system driven by yield maximisation rather than ecological balance. Small-scale farms face mounting challenges: intensive labour demands, limited access to technology, financial dependencies, and knowledge gaps in adapting to changing conditions. If they vanish, what remains is a monolithic, extractive model that prioritises short-term gains over long-term sustainability.

Precision Agriculture Technologies offer potential solutions to some of these challenges. However, they are primarily designed for large-scale, efficiency-driven farming, often reinforcing monocultures. These innovations are rooted in a techno-optimistic paradigm, assuming that automation and data-driven decision-making can uniquely address agriculture's systemic issues. Yet, when automation enters a profession, it often devalues human labour and expertise. This raises the risk of a 'technological paradox' - where technology promises optimisation but unintentionally erodes farmers' agency, knowledge, and role within the ecosystem. As the Colombian philosopher Nicolás Gómez Dávila warned:

'Civilisation nears its end when agriculture ceases to be a way of life and becomes an industry.'

- Nicolás Gómez Dávila

Agriculture, especially in the age of climate change, requires more than technological fixes. Applying new tools without considering their broader implications is merely symptom treatment, ignoring the underlying disease. This is not to dismiss the vast potential of Precision Agriculture Technologies (PATs), but to emphasise that their implementation must be holistic, ensuring that farmers remain the keystone species of the system. As Marshall McLuhan famously noted:

'We shape our tools, and thereafter our tools shape us.'

- Marshall McLuhan

The key question is not whether to adopt technology, but how we can design it in a way that empowers farmers rather than undermining them, enabling them to be both stewards and beneficiaries of their land while cultivating a thriving, resilient ecosystem.

1.2. Research Questions and Objectives

The following list presents the research questions explored and answered in this thesis.

Small-Scale Farms

RQ 1. Why should small-scale farms in Europe be preserved?
RQ 1.1. What are the biggest challenges faced by small-scale farms in Europe?

Precision Agriculture Potential

RQ 2. Why should small-scale farms adopt Precision Agriculture technologies?
RQ 2.1. What are the advantages of Precision Agriculture technologies in the context of small-scale farms?
RQ 2.2. What are the potential overlooked disadvantages of Precision Agriculture technologies in the context of small-scale farms?

Precision Agriculture Adoption

RQ 3. What are the key factors influencing the adoption of Precision Agriculture technologies among small scale farms?
RQ 3.1. What is the role of Human-Robot Interaction (HRI) in the adoption of Precision Agriculture technologies?
RQ 3.2. What strategies can be implemented to enhance trust in Precision Agriculture technologies among small-scale farmers?

Data-Driven Decision-Making

RQ 4. Which specific data points (e.g., morphological and physiological plant parameters, soil parameters, or bioindicators) provide the most actionable insights for agricultural decision-making?
RQ 4.1. What role do bioindicators and indicator species play in monitoring environmental changes and assessing ecosystem integrity?
RQ 4.2. How do temporal delays and local biases affect the reliability of bioindicators in ecosystem evaluation?

Technology

RQ 5. What functions, beyond data collection, should a carrier platform fulfil to enhance its attractiveness for small-scale farmers?
RQ 6. Which sensor technologies are best suited for collecting field data in Precision Agriculture?
RQ 6.1. Which sensor combinations offer the best trade-off between information depth and cost-efficiency in environmental monitoring?
RQ 6.2. Beyond cost considerations, what are the most critical criteria for selecting sensors in Precision Agriculture and environmental monitoring?

1.3. Approach and Methodology

Agriculture is a diverse and complex field. Developing technologies for this sector requires a thorough understanding of its many facets. To achieve this understanding, this thesis has employed various methods to gain the most comprehensive picture possible.
The research revolves around three key pillars: an exploratory literature review, quantitative empirical research conducted through an online questionnaire, and qualitative expert interviews. This thesis integrates all these findings. Due to the significant overlap among them, insights are compiled across chapters to prevent redundancy. This chapter offers an initial outline of the methods employed, citing the sources referenced in the main text.

1.3.1. Exploratory Literature Review

The literature review was conducted in an exploratory and iterative manner, without relying on a strictly predefined search strategy or fixed search query. Instead, relevant publications were identified through a stepwise refinement of search terms, continuously adapting and expanding key terms and their synonyms. The primary databases consulted included ScienceDirect (Elsevier), SpringerLink (Springer Nature), IEEE Xplore (Institute of Electrical and Electronics Engineers), and MDPI (Multidisciplinary Digital Publishing Institute). Additionally, a substantial number of sources were retrieved using the snowballing technique, where reference lists of relevant studies were analysed to identify further pertinent literature. This flexible and context-sensitive approach allowed for a comprehensive mapping of the research landscape, particularly in areas where systematic search strategies were less effective due to heterogeneous terminologies or interdisciplinary overlaps.

1.3.2. Quantitative Empirical Research (Online Questionnaire)

To investigate current farming practices and small-scale farmers' attitudes toward Precision Agriculture Technologies, a quantitative online survey was conducted in English, German and Dutch. The study was approved by TU Delft's Human Research Ethics Committee (HREC), ensuring compliance with ethical standards. Participants provided explicit informed consent, and responses were fully anonymous.

Data collection ran from January 1 to March 15, 2025, using a snowball sampling method. Initial interviewees shared the survey within their networks, supplemented by outreach in online farming communities (e.g., Reddit). To mitigate selection bias, participants were recruited from diverse communities and countries, ensuring a broad range of network diversity. The final sample consisted of 44 valid responses from active farmers and agricultural decision-makers, yielding a 52% response rate. Responses from non-agricultural participants and incomplete submissions were entirely removed from the dataset. While the study primarily targeted crop and mixed farms (see Chapter 2.1.1. Farm Types in the European Union), livestock farmers were not excluded, as Pearson and Spearman correlation analyses showed no statistically significant impact of farm type on general responses. However, for crop-specific questions, such as the number of cultivated crops, responses from livestock-only farmers were excluded. Mixed farms were included in all analyses. A more comprehensive overview of the survey participants' demographics is available in the appendix (see Appendix 7.4.1. Sociodemographics of Participants).

The survey comprised 35 questions that covered farm characteristics, PAT adoption, automation acceptance, and future technological expectations. It included open-ended, multiple-choice, and rating scales (0 - 10). Approximately one-third of the survey focused on qualitative insights. Open-ended responses were categorised and analysed thematically. A pilot test ensured clarity and reliability before deployment.
Data analysis was conducted using Jamovi and Excel, employing descriptive statistics and correlation tests (Pearson or Spearman, depending on the data distribution). Given the small sample size, a significance threshold of $p < 0.01$ was applied for statistical tests.A notable limitation is the small sample size. Since farming practices vary widely, future research should aim for a larger and more structured sample to improve representativeness.

1.3.3. Qualitative Empirical Research (Expert Interviews)

To complement the quantitative data collection and ensure a multidimensional understanding of the perspectives on agricultural and plant biology, expert interviews were conducted. The primary goal of these interviews was to explore relevant topics and relationships, supporting the quantitative data and covering additional areas such as plant biology. A total of eight experts from the Netherlands, Germany and Austria were selected based on their specialised knowledge in agriculture and agricultural sciences. The group included conventional farmers, organic farmers, regenerative agriculture practitioners, and agricultural biologists. This diverse selection ensured a comprehensive perspective on the relevant topics. Experts were recruited through targeted email inquiries and networking, providing access to a broad range of expertise from various sectors of agriculture.

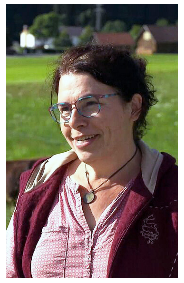
Interviews were held either in-person or through videoconferencing, based on the experts' availability. A semi-structured approach was utilised, enabling a mix of structured questions and open-ended answers. The interview guide was created from the literature review and a pilot interview to guarantee the questions' relevance and clarity. Each interview lasted an average of 70 minutes.

Interviews were recorded in audio format, and transcripts were generated only upon obtaining consent from the experts. In such instances, written notes were also taken to enhance the audio recordings. Conducted in both English and German, the transcripts were preserved in their original languages. Direct quotations used in the thesis were translated into English as needed. The Ethics Committee of TU Delft approved the study, and all participants provided informed consent. Data from experts who requested anonymity was anonymised, while those who consented were identified by name.

To minimise bias, neutral questions were used for interviews, and experts with diverse perspectives were intentionally selected to create a comprehensive dataset. Inductive coding and thematic analysis were applied to uncover key patterns and themes in the responses. The outcomes of the expert interviews were merged with insights from the online survey and literature review. This blend of qualitative and quantitative data provided a richer understanding of the explored topics.

On the next page is a concise description of each interview participant, clarifying their qualifications for the interview and outlining the topics discussed during the interview.

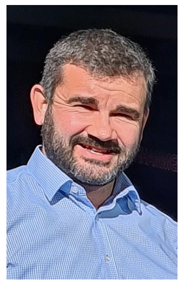
Christine Bajohr
Christine Bajohr is a German leading expert and practitioner in climate-resilient farming and sustainable land management. As co-founder of KUHproKLIMA, she applies Holistic Planned Grazing to enhance soil health and biodiversity. Managing a Demeter-certified farm in Bavaria, she integrates agroecological research into practice. A recipient of the Bavarian Climate Prize, she actively shapes EU agricultural policy, contributing to initiatives like EIP-AGRI's Healthy Soils for Europe. She also serves as managing director of AERA Land gGmbH, a nonprofit organisation dedicated to advancing regenerative land use and driving digital innovation in agriculture. In our interview, we explored the digitalisation of agriculture, focusing on satellite data, automation, and efficiency gains. We discussed the ethical dimensions of data usage, the need to protect farmers' autonomy, and the systemic changes required to ensure digital innovations support sustainable and equitable farming.



David Brunmayr
David Brunmayr is an Austrian agroecologist and co-founder of Organic Tools, a company dedicated to developing innovative technologies for market gardening, agroforestry, and ecological farming. Specialising in agricultural mechanisation and sustainable small-scale farming, he is also an active advocate for the future of small-scale agriculture, promoting the development of appropriate, farmer-centred technologies. In our interview, we explored the role of automation and AI in agriculture, particularly in data collection and management. We discussed how these technologies can enhance efficiency and sustainability while also raising critical concerns about data ownership and the risks of an overly techno-optimistic approach to agricultural development.

Urs Mauk
Urs Mauk is a German leading expert in regenerative agriculture, soil fertility, and vegetable cultivation. As the founder of ReLaVisio, he provides consultancy services to farms on agroecological principles, no-till farming, and carbon sequestration. He is also a co-founder of soil.diagnostix, a company that develops digital tools to enhance farmers' understanding and management of soil health. With a background in organic agricultural science and vegetable production, Mauk is widely recognised for his expertise in regenerative vegetable farming. Through ReLaVisio's YouTube channel, he disseminates knowledge on soil health and syntropic agroforestry. This interview explores the role of Precision Agriculture in small-scale, diversified farms, analysing how technological innovations can optimise labour efficiency while maintaining ecological integrity and how tailored solutions can support smaller farming operations.

Christian Fletschberger
Christian Fletschberger is an Austrian conventional farmer and an expert in agricultural policy and subsidy management at the Salzburg Chamber of Agriculture. His work focuses on ensuring compliance with EU Common Agricultural Policy (CAP) regulations, with particular emphasis on subsidy eligibility, land-use verification, and cross-compliance. His expertise extends to digital land monitoring and the optimisation of farm support administration, where he provides guidance to farmers on subsidy frameworks and environmental regulatory requirements. Our interview examined the economic and bureaucratic challenges within modern agriculture, including the sector's dependence on subsidies, the rising costs of agricultural machinery, and the increasing administrative complexities faced by farmers. Additionally, we explored the potential of cooperative models, such as machinery rings and neighbourhood assistance, as mechanisms to enhance flexibility and sustainability in contemporary farming systems.

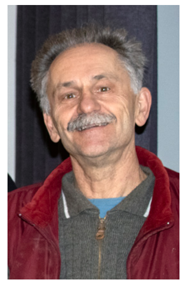


Howard Koster
Howard Koster is a Dutch regenerative farmer and a specialist in regenerative agriculture and agroecology with a Master's in Organic Agriculture from Wageningen University. He co-manages De Biesterhof, a regenerative farm in the Netherlands established in 2022. The farm employs a diversified approach - combining market gardening, arable farming, agroforestry, and food forests - to enhance biodiversity and soil health. Beyond farm management, Koster is deeply engaged in agricultural education and community outreach, offering workshops and guided farm tours. This interview examines the intersection of sustainable farming, data collection, and automation. It delves into attitudes toward technological advancements in agriculture and critically evaluates the capabilities farm robots need to effectively support regenerative farming practices.

Johann Winklhofer
Johann Winklhofer is an Austrian organic vegetable farmer and the owner of a fourth-generation organic nursery. With nearly 40 years of experience, he specialises in cultivating a diverse range of crops while integrating traditional horticultural practices with modern organic standards. His expertise lies in seasonal crop planning, soil fertility management, and sustainable greenhouse production. In this interview, Winklhofer shares insights into the complexities of managing a diversified organic farm with a direct marketing approach. He discusses the high labour demands of organic cultivation, the limitations of automation, and the necessity of efficient mechanisation in diverse farming operations.

Harriet Mella
Dr. Harriet Mella, an independent research scientist from Austria with a Doctorate in Natural Sciences, specialises in unravelling unexplained phenomena in plant growth and development. With expertise in microbiology, mycology, and biochemistry, her work advances resilient, low-input agricultural systems. As a leading educator in Carbon microcycling, she bridges biochemical research with agronomy, focusing on soil carbon sequestration, microbial-plant interactions, and nutrient bioavailability. This interview delves into the role of bioindicators in plant phenotyping and data collection, highlighting how observational systems enhance decision-making by assessing plant and soil characteristics. It also explores how bioindicators reflect ecosystem health and evaluates the hierarchy and significance of different data types in agricultural decision-making.

Gert-Jan Noij
Gert-Jan Noij is a researcher at Wageningen Environmental Research, specialising in agricultural environmental management and water quality. His work focuses on buffer strips and nutrient runoff mitigation, contributing to sustainable farming and conservation. He has co-authored studies on buffer zone effectiveness in reducing nutrient leaching into surface waters. His expertise in nutrient management and soil-water interactions informs agro-environmental policy. This interview explores automation in agriculture and the role of data collection, particularly soil data. It examines how precision monitoring can enhance environmental sustainability while balancing technological reliance with ecological land management.



1.4. Stakeholders

This study employed Mendelow's Matrix to analyse stakeholders by categorising them according to their power and interest in the project. This method effectively informs stakeholder management by determining which groups require engagement, need to be kept satisfied, should be kept informed, or only require monitoring.

A total of 24 stakeholders were identified for this master's thesis. Given the complexity of managing such a large group, a pairwise ranking method, using a tournament-style format, was applied to establish a priority order from 1 to 24. Stakeholders were systematically compared in pairs, with iterative selections leading to a final structured ranking. This method simplified the prioritisation process by reducing it to binary decisions. The resulting rankings—power (vertical axis) and interest (horizontal axis)—were then mapped onto Mendelow's Matrix. Subsequent research considered key stakeholders, highlighted in blue (see Figure 01).

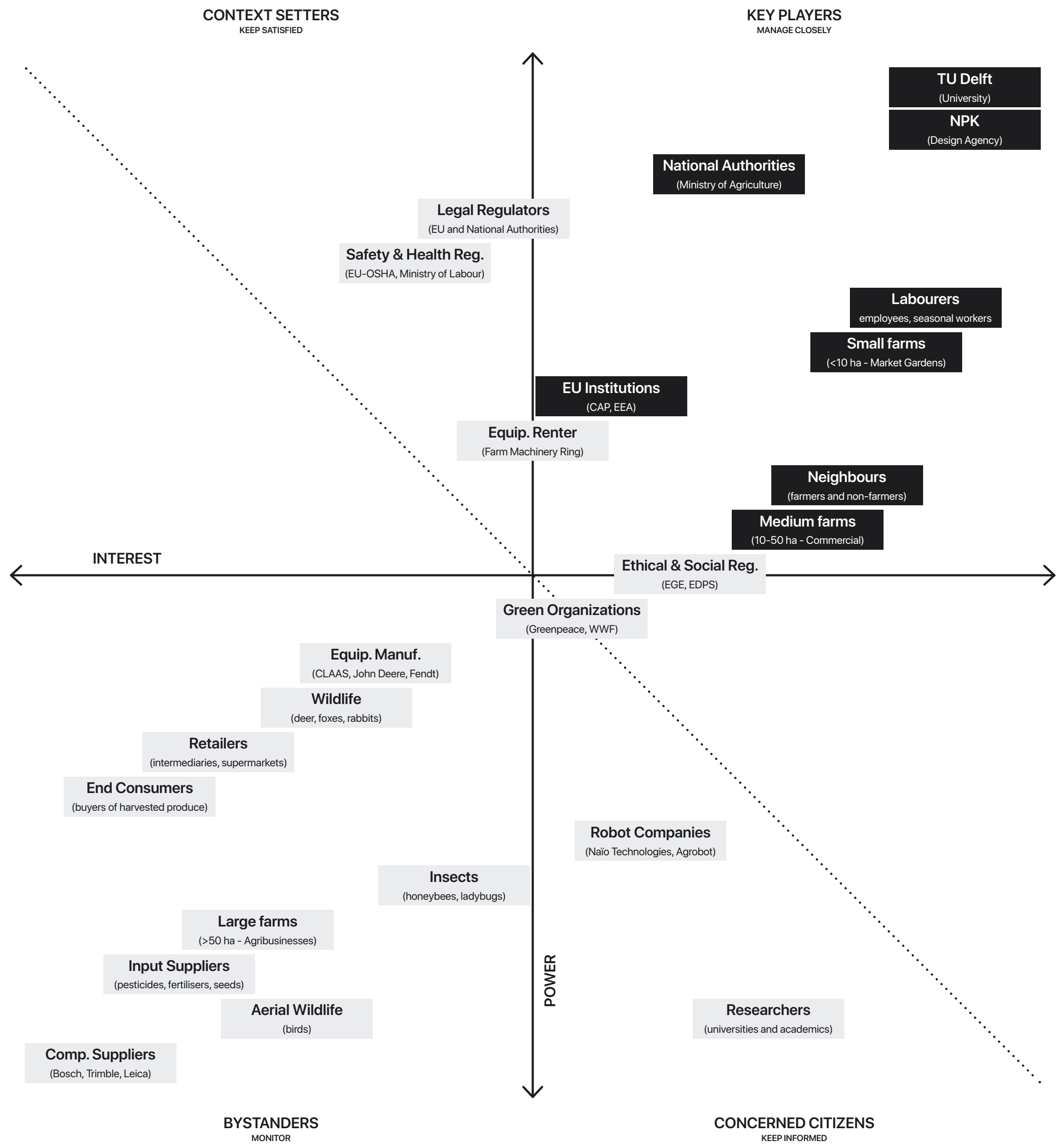


Figure 01: Stakeholder Map

1.5. Project Scope

Since agriculture is an enormously broad topic, the scope of this work must narrow it down. At its core, the focus is on understanding what technological innovation should look like for small-scale farms and how a modular platform can support this. The primary focus is on data-driven technologies and how field data collection can provide meaningful support. While the mobile platform, the "micro-tractor", is the centrepiece of the development, additional extension modules are also being considered. The graph illustrates the distribution of focus in this work (see Figure 02).

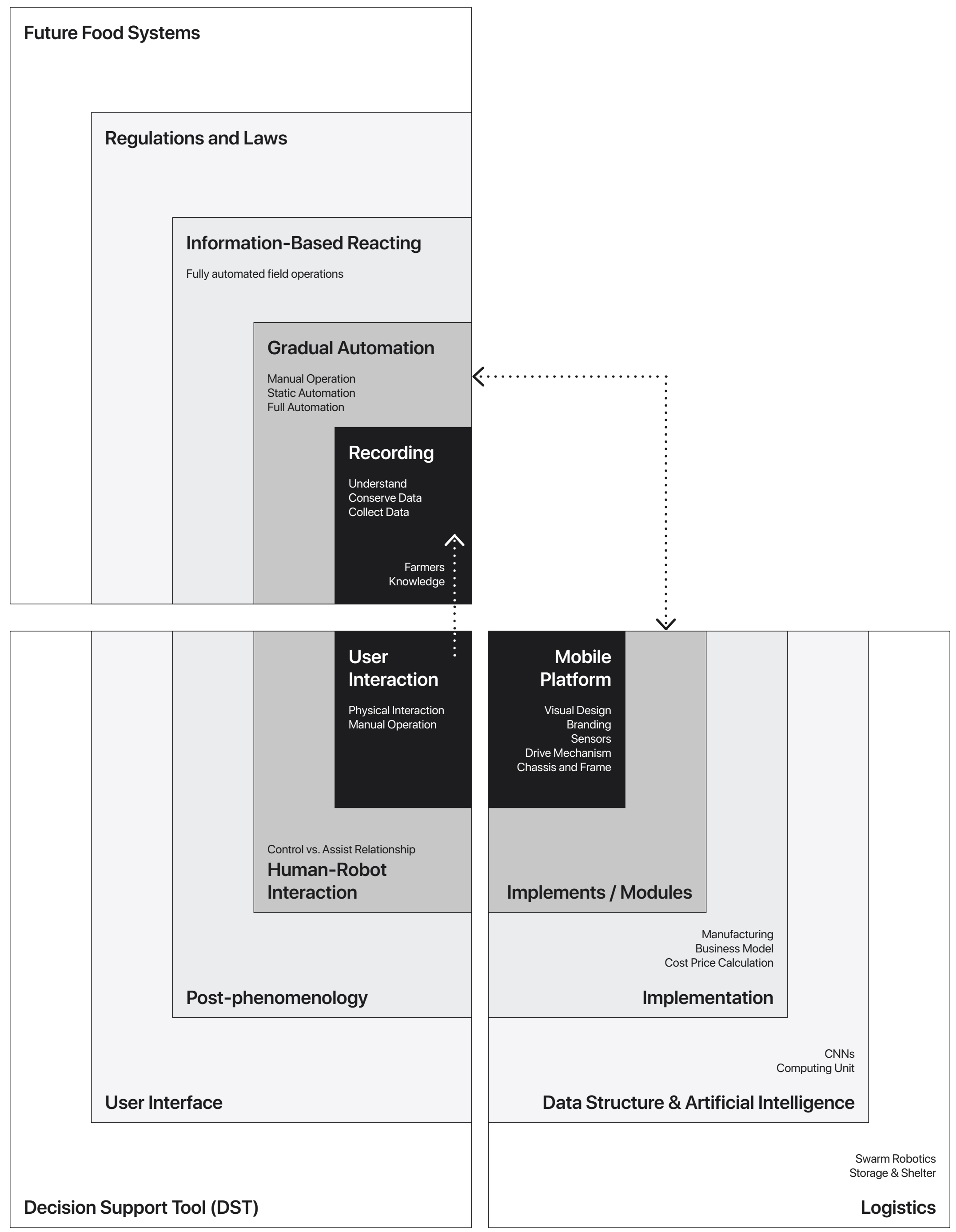


Figure 02: Project Scope

Chapter 2

Research

Figure 03: Aerial view of the landscape (Freepik, n.d.)

2.1. Agriculture

Agriculture is a cornerstone of human development, contributing significantly to Gross Domestic Product (GDP) while maintaining ecological balance and ensuring nutritional security (Devlet, 2020). It plays a crucial role in achieving food security and advancing the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger), along with other interrelated objectives (Viana et al., 2022). However, rapid population growth is placing increasing pressure on agricultural resources, necessitating higher food production to meet rising demand (Dhillon & Moncur, 2023). This intensifies the strain on agricultural systems, resulting in severe environmental consequences (Monteiro et al., 2021).

This chapter starts with an introduction to agriculture in the European Union. To understand how technological innovation can enhance the resilience and sustainability of small-scale farms, it is first necessary to know what they are, explore their main challenges and understand their root causes. The chapter focuses on small-scale farms and answers the following research questions:

RQ 1. *Why should small-scale farms in Europe be preserved?*

RQ 1.1. *What are the biggest challenges faced by small-scale farms in Europe?*

2.1.1. Farm Types in the European Union

In the context of the European Union, a farm is defined as a single unit of land and operations managed collectively for agricultural purposes, whether as a primary or secondary activity (Eurostat, 1001). A farm may consist of multiple parcels of land, which together determine its total size and productive capacity.

Farm typologies provide a structured framework for understanding the diversity of agricultural systems. They are essential for policymakers, including those shaping the Common Agricultural Policy (CAP) of the European Union, to differentiate between farm types and design targeted incentives accordingly (European Union, 2022a). By categorising farms based on distinct characteristics, typologies ensure that agricultural policies effectively address the diverse structural realities of the sector (Huber et al., 2024).

Farm Types (Based on Standard Output)

Agricultural structures across the European Union vary significantly in terms of size, production methods, and economic viability (Beckers et al., 2018; Eurostat, 2022). To facilitate standardised comparisons, the EU Farm Typology Classification System, developed under the CAP, categorises farms according to two key criteria: the type of agricultural activity and the economic scale of operations. This classification relies on the concept of Standard Output (SO), which represents the average monetary value of agricultural production per hectare or per head of livestock (European Union, n.d.; Eurostat, 1002). The SO metric provides a standardised approach to assessing farm productivity and enables policymakers to design CAP measures that align with the specific needs of different farm types (Eurostat, 1002).

The EU Farm Typology Classification System identifies three main farm types based on Standard Output (SO):

Crop Specialists
Farms where at least two-thirds of the total output or economic size comes from a single crop-related activity.

Livestock Specialists
Farms where at least two-thirds of total output comes from a specific type of livestock production.

Mixed Farming Operations
Farms engaged in multiple activities, with no single activity dominating output.

In 2020, crop specialist farms accounted for 58.3% of all EU farms, with field cropping as the largest subgroup at 34%. Specialist livestock farms represented 21.6%, including 5.1% dedicated to dairy production. Mixed farms made up 19.3%, while a small fraction remained unclassified (Eurostat, 2022) (see Figure 4).

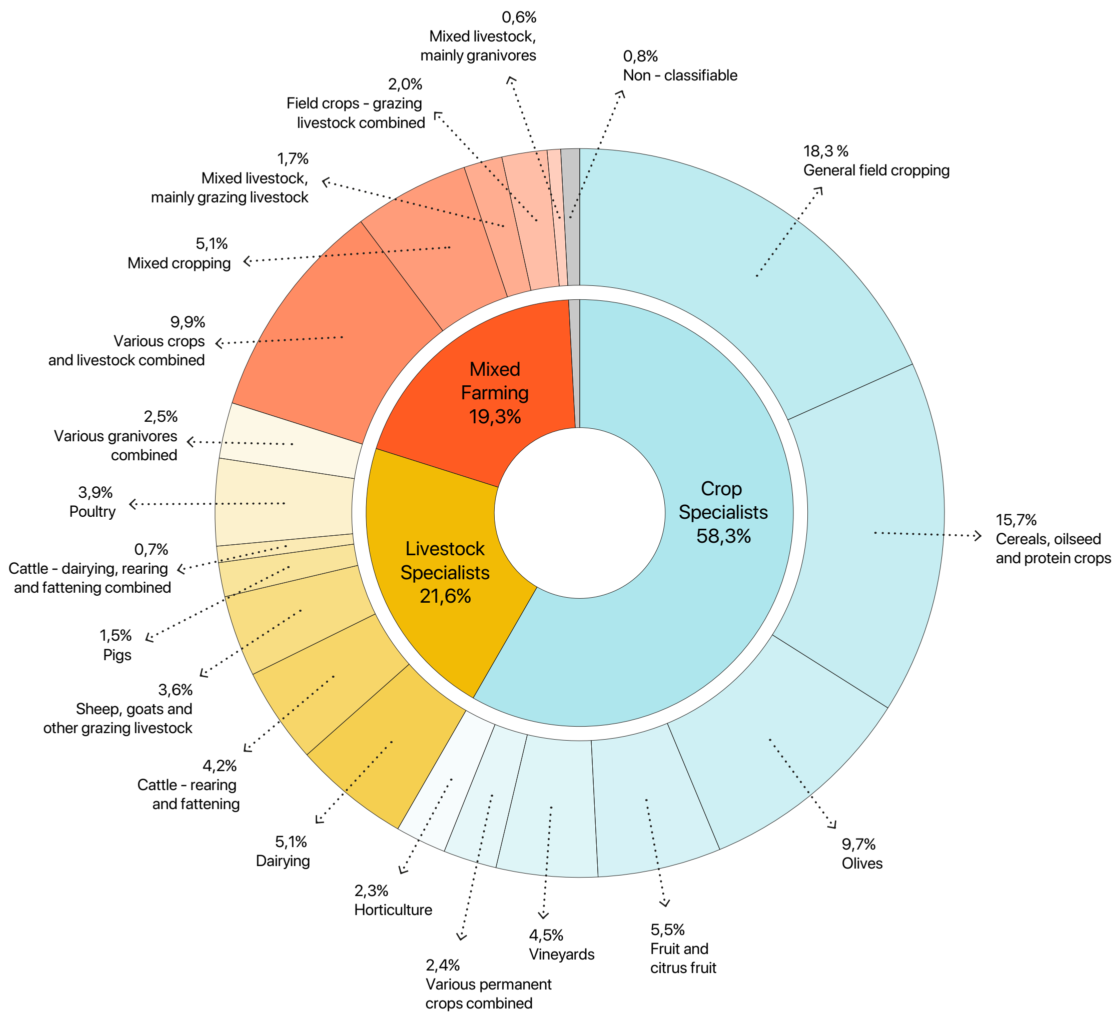


Figure 04: Farms by type of specialisation (share of EU farms,%,2020); Created by the author based on (Eurostat, 2022)

2.1.2. Small-Scale Farms

This chapter lays a foundation by exploring the quantity and geographic spread of small-scale farms in Europe and the key crops they cultivate. It wraps up by emphasising the essential contribution of small-scale farming to the agricultural sector and its wider importance for food security, clarifying why these farms are the focal point of the thesis.

This research defines small-scale farms primarily by their size, specifically focusing on those up to five hectares, in accordance with EU definitions. However, due to differing commonly accepted definitions and variations in available data, some graphs adopt a ten-hectare threshold, as per the FAO definition. The term smallholder is used interchangeably with small-scale farm throughout this research, applying the same definition. (For a more detailed definition of 'small-scale farm', 'smallholder', 'small-scale farm', and 'family farm'; see Appendix 7.2. Terminology of Small-Scale Farms).

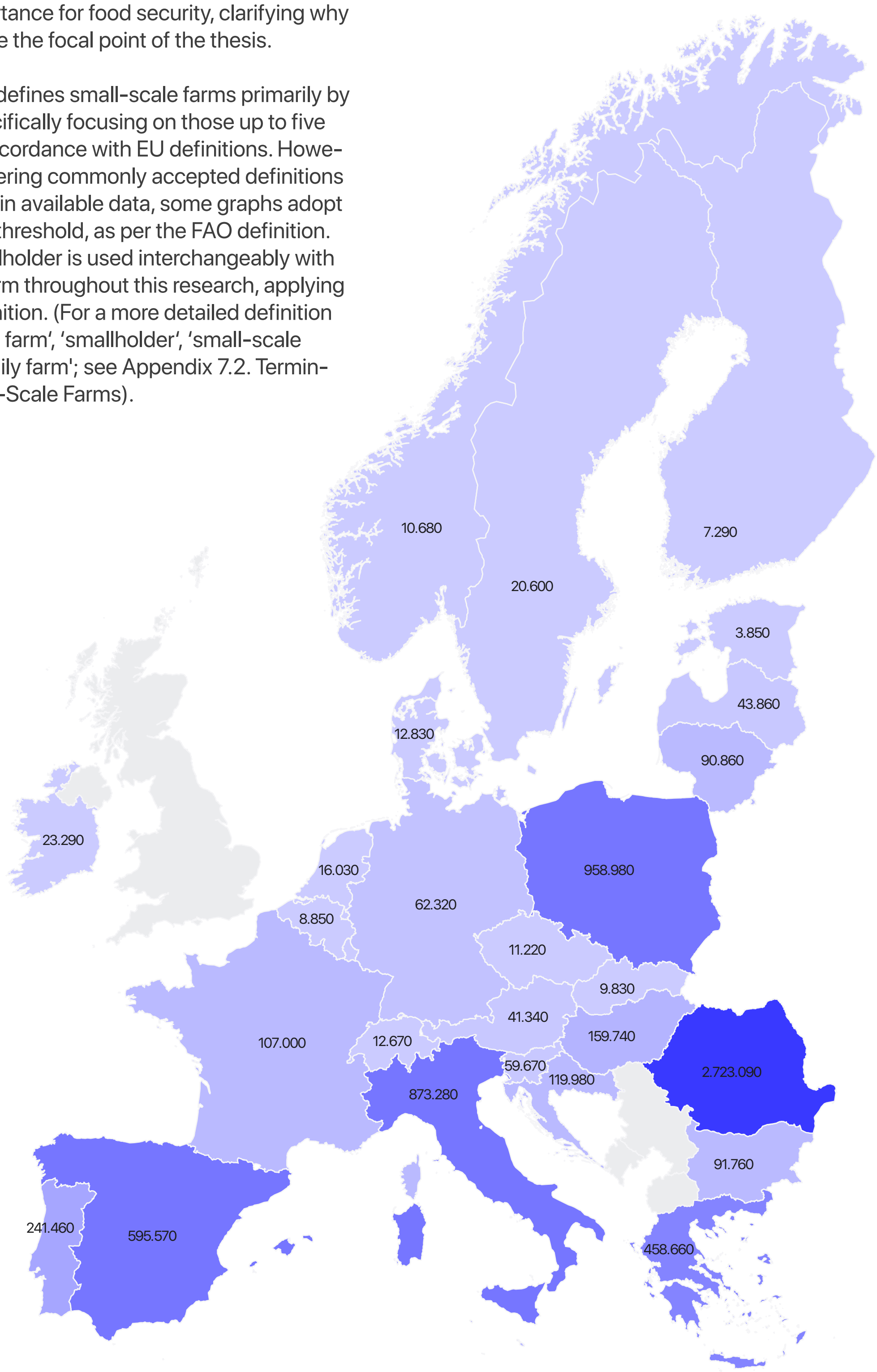


Figure 05: Amount of Farms <10ha in 2020 per Country; Created by the author based on (Eurostat, 2022)

2.1.2.1. Distribution

Globally, most farms are small in land area, with approximately 84% covering less than two hectares (Lowder et al., 2016). In the European Union, 63.7% of farms in 2020 had less than five hectares of agricultural land (Eurostat, 2022). Additionally, two-thirds of these small EU farms operated on fewer than two hectares (Rossi & EPRS, 2022).

Luxembourg (53.8%) and Iceland (82.7%) are the only European countries where most agricultural holdings surpass 50 hectares. In contrast, the majority of farms in other EU member states are under this size. The accompanying bar chart (see Figure 06) illustrates the dominance of small-scale farms throughout Europe, with Romania standing out as leading in the number of such holdings.

The accompanying map (see Figure 07) provides the number of farms under 10 hectares across each EU country as of 2020, giving further insight into the prevalence of small farms. The data indicates that these small farms form the backbone of European agriculture. Thus, they represent the largest and most critical target audience for agricultural innovation. Tailoring solutions to their unique requirements presents the greatest opportunity for transformative change within the sector.

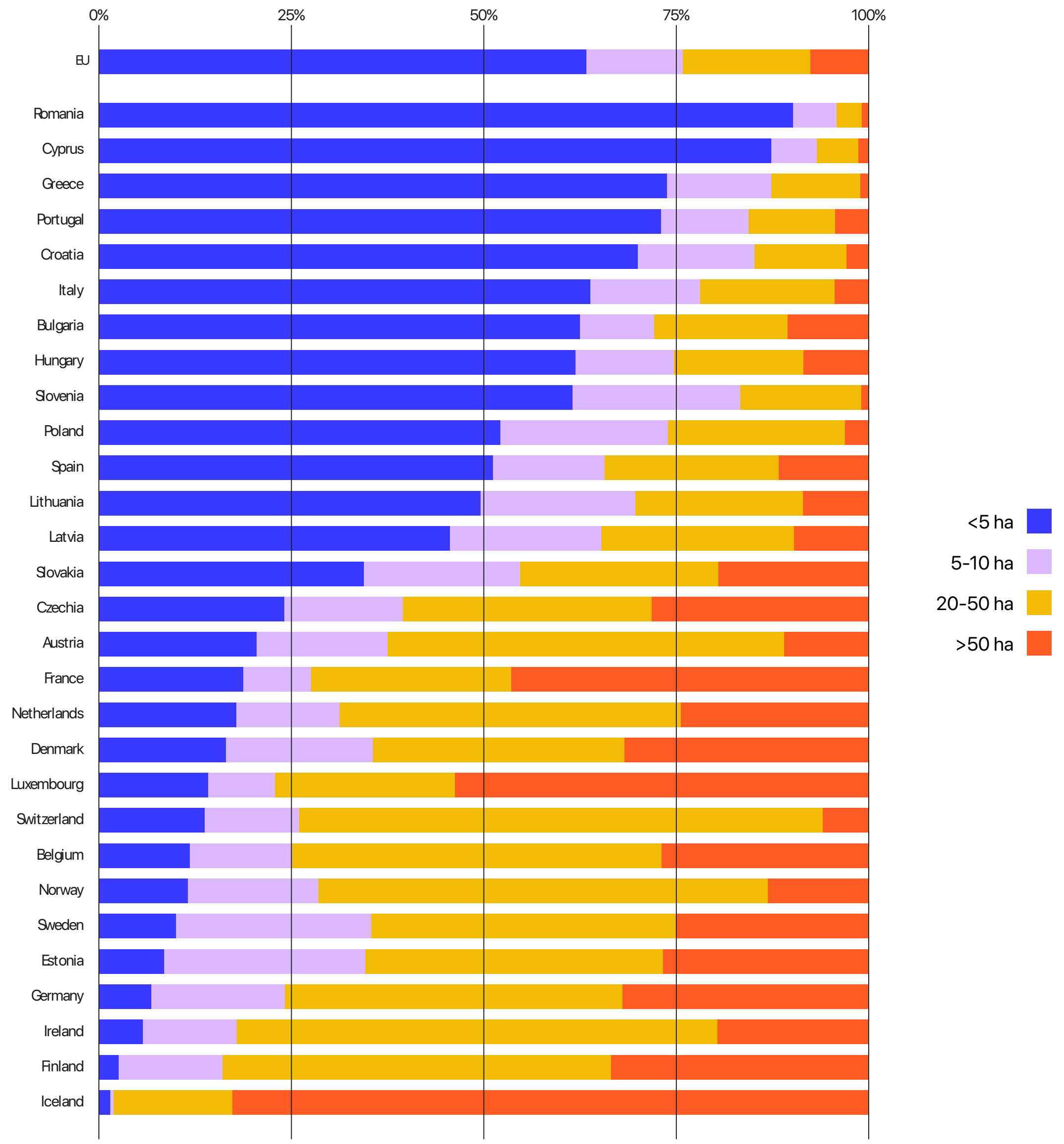


Figure 06: Distribution of different Farmsizes in 2020 per Country; Created by the author based on (Eurostat, 2022)

2.1.2.1. Crops and Diversification

In the EU, small-scale farms (under 5 hectares) primarily grow permanent crops (Eurostat, 2020). It is difficult to define the crops grown by small-scale farms, as the smaller the farm, the greater the diversity of crops cultivated (Ricciardi et al., 2021; Rossi & EPRS, 2022) . Small-scale farms generally maintain more diversified crop portfolios compared to larger operations. (SALSA Consortium, 2020).

Figure 07: Diversified Market Gardening in Practice (Market Garden Pro, 2025)

Benefits of Crop Diversification

Crop diversification offers multiple advantages for small-scale farms. It enhances resilience against pest infestations (Weigel et al., 2018), improves overall yields (Clough et al., 2020; Di Falco et al., 2010) and reduces dependency on chemical fertilisers (Bommarco et al., 2013; Clough et al., 2020; Weigel et al., 2018).

Expert interviews further emphasise its role in mitigating financial risks. Losses from one crop, caused by drought, pests, or market fluctuations, can be offset by profits from other cultivated crops. Additionally, growing plant species with diverse environmental requirements increases resilience against extreme weather events such as droughts, floods, or frost, thereby enhancing long-term farm stability (Expert Interviews, 2025).

Beyond economic benefits, diversification promotes biodiversity within agricultural ecosystems (Clough et al., 2020; Rossi & EPRS, 2022) and can lead to increased productivity despite lower resource inputs (Bommarco et al., 2013). Farmers implement diversification through two primary strategies. The first involves crop rotation, where different crops are grown sequentially on the same land to maintain soil health and reduce pest pressure. The second approach is spatial diversification, where multiple crops are cultivated simultaneously across different sections of the farm, enhancing biodiversity and mitigating risks (Weigel et al., 2018). Crop diversification plays a crucial role in ensuring the long-term sustainability of small-scale farms by reducing their vulnerability to economic and environmental uncertainties.

2.1.2.2. Mechanisation and Equipment

To understand the advantages of technology implementation, we should initially examine the tools that farmers use in their fields. Small-scale farmers throughout Europe employ a variety of machinery designed to meet their agricultural needs. Generally, this equipment features a mobile platform that can be either manually operated (like a wheel hoe) or motorised (such as a tractor), along with an attachment known as an implement (for example, a plough) (see Figure 08).

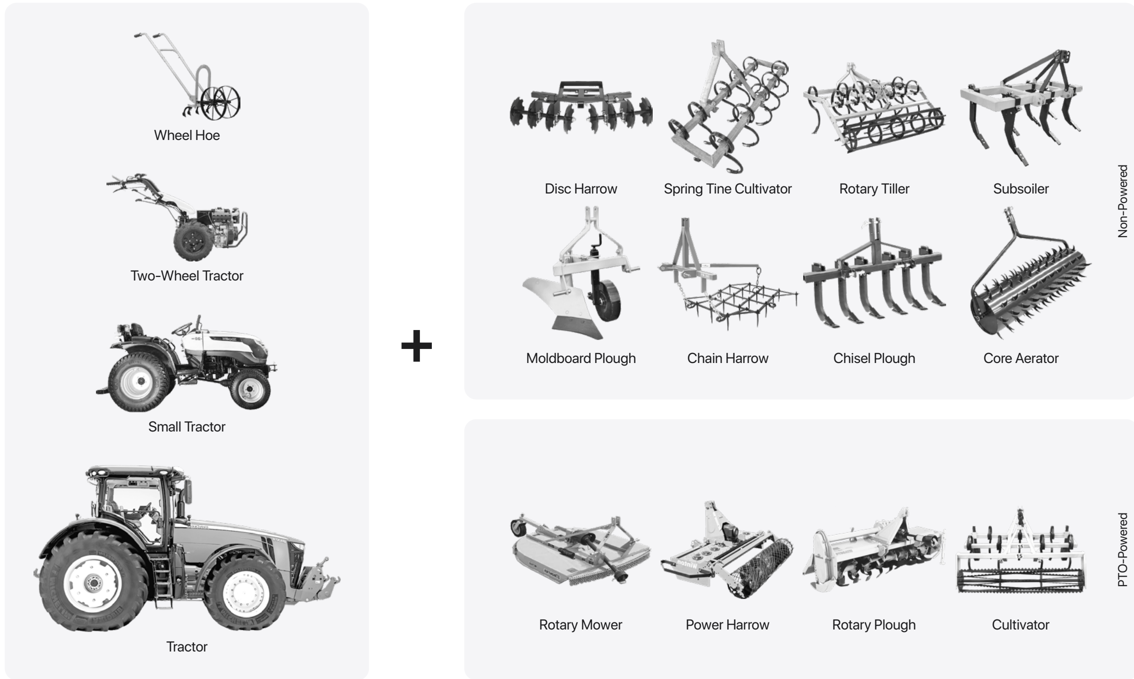


Figure 08: Standard Setup of a Farmer

The Mobile Platform

The mobile platform - whether a four-wheel tractor, a single-axle machine, or another towing device - serves as the foundation of agricultural mechanisation. Among these, tractors of all sizes play a crucial role in farming due to their versatility and adaptability to different configurations (Mocera et al., 2023). While large-scale commercial agriculture increasingly relies on heavy, high-powered tractors, small-scale farms often prefer two-wheel tractors (see Figure 09).

Figure 09: Topview - Big Ag Setup; Changed by author based on (Elevate, 2024)

Figure 10: Topview - Small Farm Setup; Changed by author based on (Organic Tools, n.d.)

Two-Wheel Tractors

Two-wheel tractors, also referred to as walk-behind tractors, single-axle tractors, walking tractors, or hand tractors, are compact agricultural machines designed as single-axle counterparts to traditional four-wheel tractors (see Figure 11). Typically powered by small gasoline or diesel engines, these versatile machines can operate multiple implements using a single power source, offering a cost-effective and efficient solution for small-scale farmers.

This affordability extends to both the tractor and its implements. Implements made for conventional four-wheel tractors, especially those needing a power take-off (PTO), are usually far more costly than those for walk-behind tractors. Moreover, maintenance expenses are typically lower since walk-behind tractors are generally simpler to repair (Frost, 2023).

Beyond their financial advantages, two-wheel tractors are particularly well-suited for small-scale farms due to their efficiency in managing compact or irregularly shaped plots. Large, conventional machinery is often impractical in these settings, making smaller, more manoeuvrable equipment a better fit for small-scale operations (Al-Amin et al., 2022). Furthermore, the high cost of large tractors remains a significant barrier for many small-scale farms, whereas two-wheel tractors provide an adaptable and affordable solution for a wide range of agricultural tasks (Kornecki & Reyes, 2020).

Expert interviews reinforce these insights, emphasising the economic and functional benefits of these machines. The carrier platform—Wbe it a four-wheel tractor, a single-axle machine, or another towing device—serves as the core of agricultural mechanisation. An ideal carrier platform should be compatible with a variety of implements, enabling farmers to undertake different agricultural activities without the need to completely revamp their machinery inventory. This modular approach lowers costs, enhances flexibility, and fosters technological advancement, allowing farms to adjust to evolving agricultural demands (Expert Interviews, 2025).

'In traditional arable and vegetable farming, you use many different tools, but the tractor is central. I would say a carrier platform, to which I can attach various devices, is the key piece of equipment. Then there are different planting technologies and implements, which are extremely specific depending on the branch of the operation.'

- Expert Mauk

The two-wheel tractor market is growing rapidly, driven by increasing demand and innovations like electric motors and Precision Agriculture features. Electric models are preferred for their quiet operation and environmental benefits, supporting the global shift toward sustainable agriculture. This ongoing innovation will further boost market adoption (MWR, 2025).

Figure 11: Farmer with Two-Wheel Tractor (Bellm, 2023)

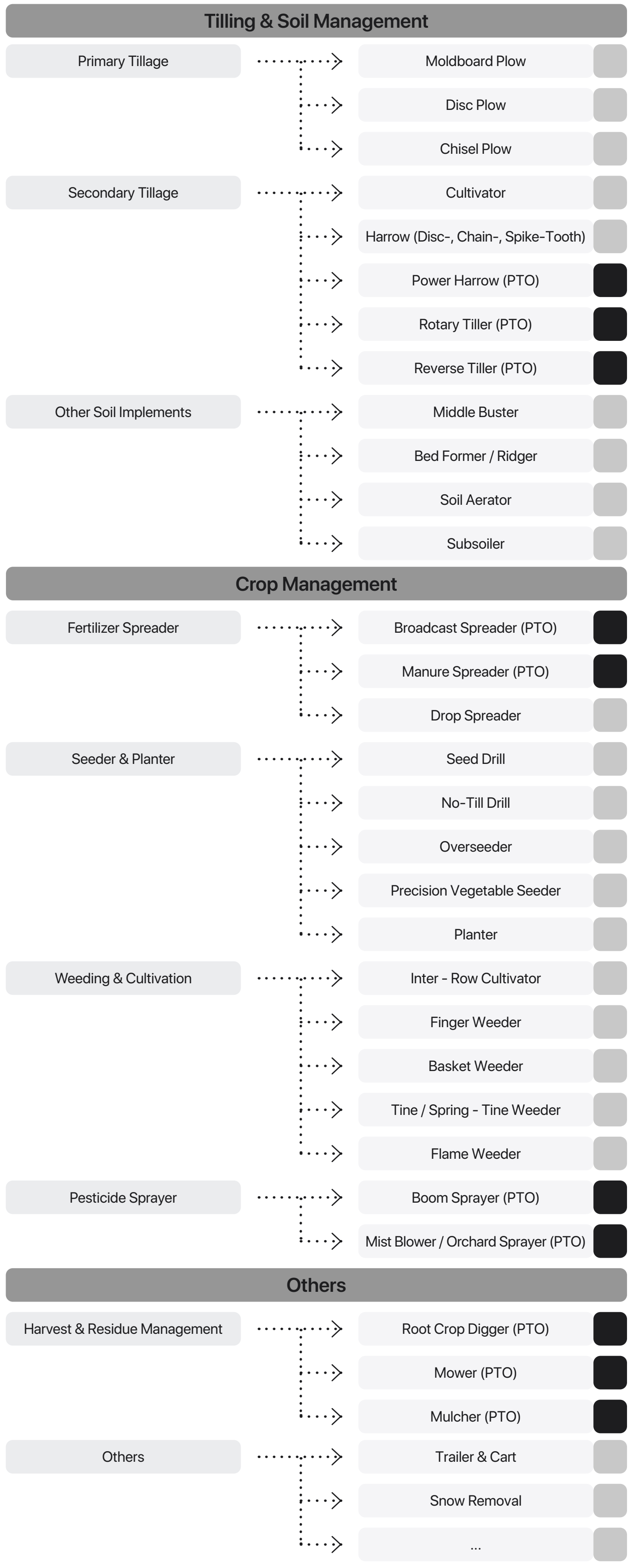


Figure 12: List of Commonly Used Implements

Implements

Agricultural implements are vital tools for a carrier platform, enhancing its capabilities for specific farming tasks. Some, like ploughs and planters, are passive and pulled or ground-driven, while others, such as mowers, have powered components using the tractor's powertrain. Powered implements draw energy from the power take-off (PTO) system, which is common in modern tractors (Mocera et al., 2023).

Farmers use various implements, from basic attachments to highly specialised machinery, depending on farm size, crop type, and operational needs. Figure 12 provides an overview of the most commonly used implement types. Naming conventions for implements vary across countries and regions, and translations may differ accordingly. Additionally, the design and dimensions are influenced by the carrier platform. For example, a plough designed for a high-horsepower tractor differs significantly in scale and structural requirements from one intended for a manually operated wheel hoe (Frost, 2023).

This summary, based on multiple sources (Barkolias, 2023; BCS, n.d.; Deere, n.d.; Köppl, n.d.; Lipco, n.d.), provides a general overview rather than an exhaustive classification. As noted, some implements require PTO power while others do not. Those have been marked in the overview (see Figure 12).

2.1.2.3. The Importance of Small-Scale Farms

Small-scale farms form the backbone of agricultural systems worldwide, particularly in local food production and rural economies (Dhillon & Moncur, 2023; Guth et al., 2022). Although industrial agriculture dominates in terms of global food output, small-scale farms play a crucial role in preserving genetic diversity, maintaining resilient ecosystems, and sustaining communities. In an era defined by globalisation, farm specialisation, large-scale production, and a widening disconnect between rural communities and agriculture, these smaller farms may appear outdated or inefficient. Nevertheless, they are indispensable for sustaining local economies and preserving ecosystems (Guth et al., 2022).

A key strength of small-scale farms lies in their structural diversity and varied farming practices, which foster high levels of biodiversity and enhance ecological resilience (Babai et al., 2015; Marini et al., 2009; McDonagh et al., 2017). This diversity is also vital for mitigating risks associated with nutritional deficiencies, ecosystem degradation, and climate change (Herrero et al., 2017). Beyond food security, small-scale farming generates numerous direct and indirect benefits - environmental, social, cultural, and economic - by improving crop diversification, job security, and self-sufficiency (Dhillon & Moncur, 2023). Small-scale farms also support greater non-crop biodiversity, for instance by providing habitat at landscape edges, and typically achieve higher yields per hectare compared to larger farms (Clough et al., 2020; Ricciardi et al., 2021; Rossi & EPRS, 2022).

In addition to their role in promoting biodiversity, small-scale farms help prevent soil erosion by maintaining meadows and pastures, particularly in mountainous regions (Tasser et al., 2007). Through these practices, they stabilise landscapes and protect against land degradation, providing a valuable environmental service that bolsters resilience against both ecological and climatic challenges.

Empirical research also suggests a strong link between field size and biodiversity: smaller fields generally harbour a greater variety of species (see Figure 13) (Clough et al., 2020). Traditional small-scale farms, which often rely on more diverse cropping systems and lower levels of chemical inputs, consistently exhibit higher levels of species richness than large, highly intensive farms (Marini et al., 2009). For example, Belfrage et al. (2005) found that small organic farms hosted 56% more bird species than larger organic farms, despite both types avoiding pesticide use. This evidence underlines the need to consider farm size, alongside farming practices, when assessing the impact of agriculture on biodiversity.

> *'Small field sizes are of utter importance to halt and maybe even reverse the decline in biodiversity in landscapes.'*
> - (Clough et al., 2020)

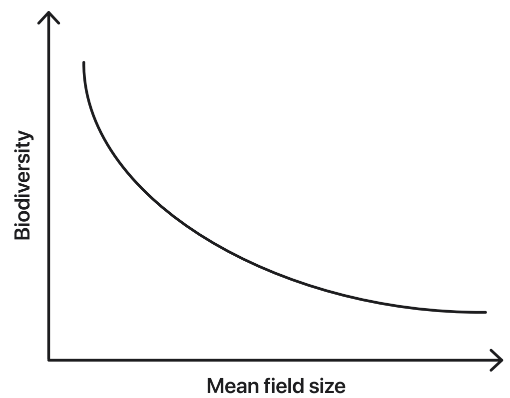


Figure 13: Link between Field Size and Biodiversity; Created by the author based on (Clough et al., 2020)

Taken together, these findings highlight the essential role of small-scale farms in modern agriculture. Their ability to support local economies, preserve genetic resources, protect biodiversity, and stabilise landscapes demonstrates that small-scale farms are not relics of the past but rather critical contributors to a more resilient and equitable future food system. As pressures from climate change, biodiversity loss, and economic restructuring increase, the necessity of maintaining and supporting small-scale farming systems becomes ever more apparent.

2.1.3. Challenges and Changes

The agricultural sector in the European Union (EU) has undergone significant structural transformations in recent decades, marked by a notable decline in its share of the overall economy in terms of both income and employment (Anderson, 2010; Beckers et al., 2018; Corsi et al., 2021; FAO, 2000; Lowder et al., 2016; Rossi & EPRS, 2022). Several factors have contributed to these changes, including technological advancements (Babalola et al., 2023; Jouzi et al., 2017; SALSA Consortium, 2020), labour dynamics (Dhillon & Moncur, 2023; Fan & Chan-Kang, 2005; Sutherland, 2023), and subsidy structures (Rossi & EPRS, 2022).

Agricultural structures are closely linked to subsidies and political measures. This is a crucial topic, as the survival of small-scale farms in Europe is significantly shaped by subsidies, though their impact varies depending on regional differences and farm types. Many survive primarily through financial subsidies rather than economic self-sufficiency (Al-Amin et al., 2022). (For more information about subsidy schemes, regulations, and farmers' perceptions based on expert interviews, see Appendix 7.3. Subsidies and Regulations).

2.1.3.1. The Decline of Small-Scale Farms

Small-scale farms play a vital role in society and the environment (see Chapter 2.1.2.3. The Importance of Small-Scale Farms), yet their numbers are shrinking alarmingly. Between 2005 and 2020, more than a third (37%) of farms smaller than five hectares disappeared. At the same time, the average farm size has increased. Despite this sharp decline in small-scale farms, the total utilised agricultural area (UAA) has remained almost unchanged, growing by just 0.3%. This shows that agricultural land is increasingly being concentrated in the hands of fewer, larger farms (Eurostat, 2022).

This trend is not unique to agriculture. Similar shifts have occurred in the industrial and service sectors, where larger businesses have grown by taking advantage of economies of scale. However, unlike in these sectors, agriculture has not seen the rise of new businesses but rather the absorption of smaller farms into larger ones, leading to a dramatic restructuring of the farming landscape (Beckers et al., 2018; Corsi et al., 2021).

Data obtained from the Eurostat Agriculture Database underscore the seriousness of this trend. The dataset [ef_m_farmleg], entitled "Farm indicators by legal status of the holding, utilised agricultural area, type and economic size of the farm, „ offers detailed statistics on EU farms, organised by size, legal form, farm type, economic output, and region (Eurostat, 2024). From this dataset, the number of registered holdings smaller than 10 hectares was obtained for the years 2010 and 2020. The percentage change over this period was calculated and represented in a graph (see Figure 14). The findings depict a concerning situation. A comparison of farms with under ten hectares between 2010 and 2020 indicates a steep decline in nearly all EU Member States, with the significant exceptions of Czechia and Denmark. In Bulgaria, for instance, the count of small farms has decreased by more than 70% in just ten years. Likewise, the Netherlands has lost nearly half of its small-scale farms in the same period. This troubling trend is depicted in Figure 14, highlighting the widespread reduction of small-scale farms throughout Europe.

The decline stems from intricate, interrelated economic, environmental, and social challenges that complicate the survival of small-scale farmers. The following chapter will examine these factors in greater depth, drawing on insights from existing literature, quantitative analysis, and qualitative research.

+51%	Czechia
+35%	Denmark
-5%	Slovenia
-8%	Spain
-8%	Portugal
-10%	Ireland
-10%	Sweden
-13%	Latvia
-14%	Cyprus
-15%	Germany
-16%	Norway
-17%	Poland
-25%	Romania
-28%	Luxembourg
-28%	Greece
-32%	Switzerland
-36%	Italy
-36%	Belgium
-39%	France
-42%	Finland
-42%	Lithuania
-42%	Croatia
-43%	Austria
-44%	Slovakia
-45%	Netherlands
-56%	Iceland
-63%	Estonia
-67%	Hungary
-73%	Bulgaria

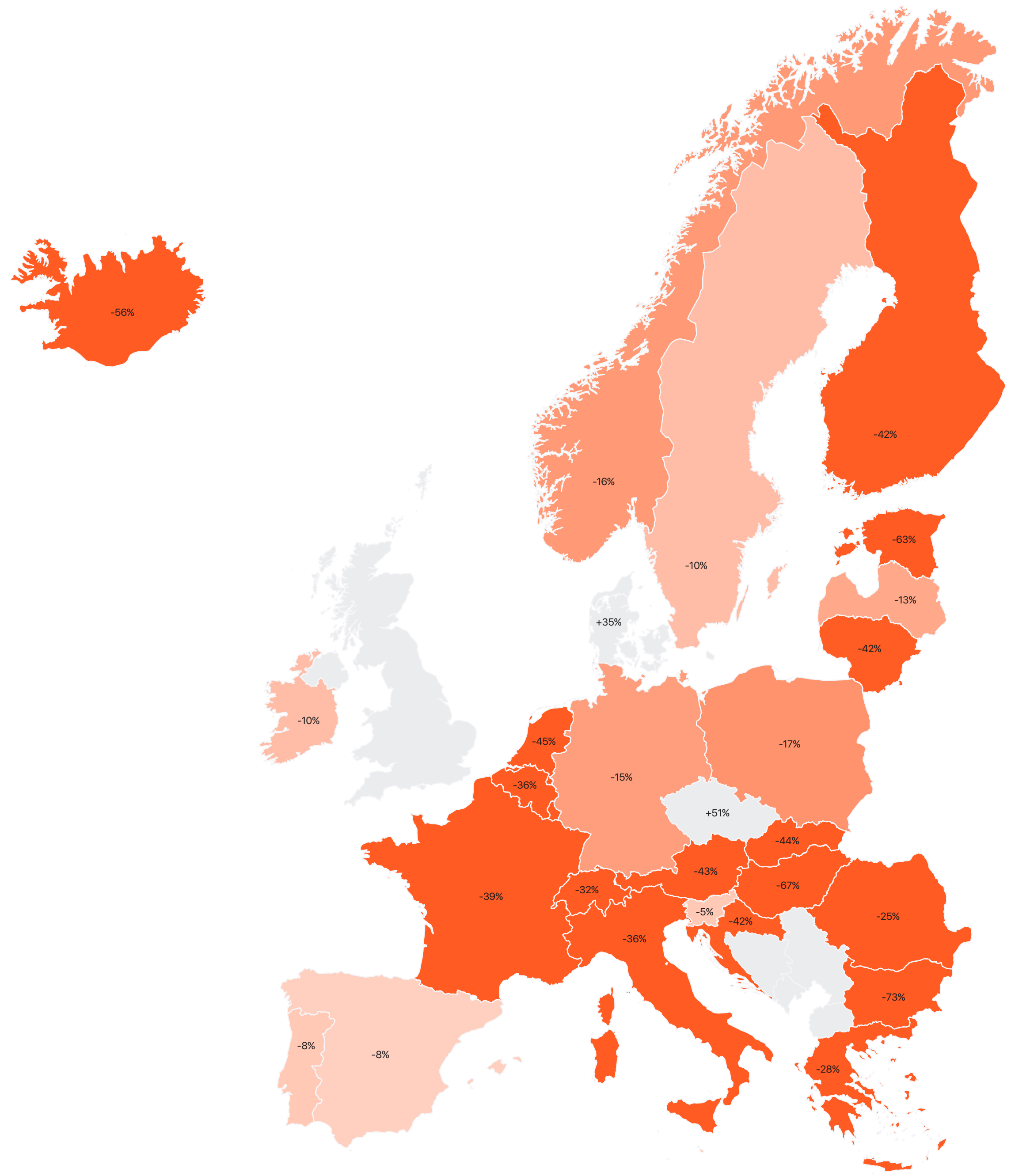


Figure 14: Decline of Small Farms (<10ha) from 2010-2020; Created by the author based on [ef_m_farmleg__custom_17007441] (Eurostat, 2024)

2.1.3.2.Main Challenges of Small-Scale Farms

Small-scale farms face several key challenges, as highlighted in the literature. These challenges can be broadly categorised into labour and workload (Jouzi et al., 2017; SALSA Consortium, 2020), regulations and bureaucracy (Babalola et al., 2023; Jouzi et al., 2017; SALSA Consortium, 2020), market access and pressures (Jouzi et al., 2017; Rossi & EPRS, 2022), the need for greater engagement in technology and mechanisation (Jouzi et al., 2017; Rossi & EPRS, 2022), and the growing impact of climate change (Dhillon & Moncur, 2023; Rossi & EPRS, 2022; SALSA Consortium, 2020).

These challenges are evident in both the quantitative survey and expert interviews. The following graph (see Figure 15) shows how participant responses were distributed across various problem categories. Many farmers reported facing multiple challenges across different areas. The graph indicates the total number of participants who identified each category as one of their most significant challenges (Quantitative Research, 2025). To minimize bias, the question was posed in an open-ended format: "What are the biggest challenges for your farm?" The written responses were then analyzed and grouped into categories. The chart provides an overall summary of these problem areas and shows how many participants (n=44) mentioned challenges related to each category.

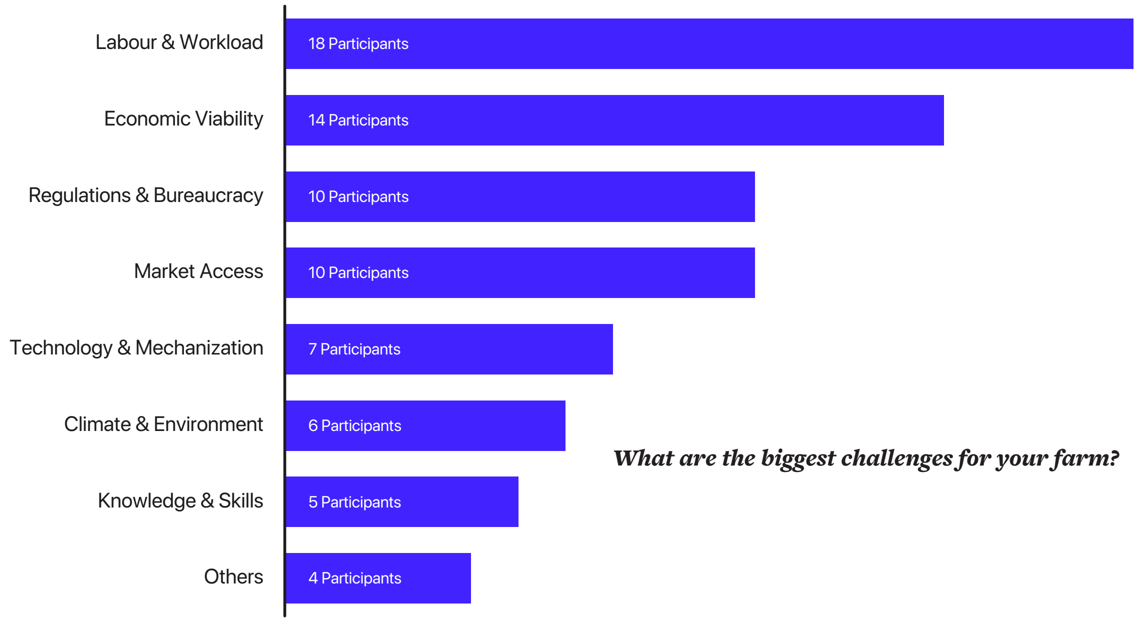


Figure 15: Key Challenges Faced by Small-Scale Farms: Findings from Quantitative Research (n=44)

Participants express significant concerns regarding high labour demands, administrative challenges, rising costs, and time limitations, especially for part-time farmers. Many respondents highlighted that increased expenses for energy, machinery, and infrastructure are not balanced by fair producer prices. Additionally, labour shortages, worsened by the seasonal nature of agriculture and the ongoing need for retraining, strain farm operations. Market distortions, including low farmgate prices and insufficient consumer awareness, hinder profitability. Concurrently, the adoption of technology presents challenges, as the costs and practicality of automation and mechanisation often do not align with the needs of smaller farms. Moreover, environmental uncertainties and the slow learning processes typical of seasonal production add further complexity, making it increasingly difficult to maintain a balance between economic sustainability and ecological responsibility (Quantitative Research, 2025).

The upcoming sections will explore each of these seven problem categories in detail, combining insights from quantitative research, existing literature, and qualitative studies. This comprehensive approach provides a detailed understanding of the challenges small-scale farms encounter, many of which are interconnected and influence each other in various ways.

Challenge 1 - Labour & Workload

Labour shortages and increasing workloads pose a significant challenge for European small-scale farms. The availability of agricultural workers is becoming an increasing concern (Sutherland, 2023). The decline of small-scale farms, alongside the consolidation of land into larger enterprises, has further exacerbated this issue (Guth et al., 2022). Traditionally reliant on family labour, many small-scale farms now face an ageing workforce and a lack of young successors willing to take over farming operations (Recanati et al., 2019). Labour availability is also a key barrier preventing new farm enterprises from being established, as the difficulty in securing workers represents a major challenge for prospective farmers (Dhillon & Moncur, 2023).

Quantitative research highlights labour-related difficulties as one of the most urgent concerns, with 44% of surveyed farmers (see Figure 15) identifying them as a primary issue (Quantitative Research, 2025). Expert interviews further reinforce these findings, emphasising ongoing struggles with heavy workloads and securing a reliable workforce.

The persistent labour shortages in agriculture stem largely from the high demand for manual work, particularly in organic and diversified farming, where mechanisation is often unfeasible. Compared to industrialised farms that utilise advanced machinery and automated systems, tasks like weeding, planting, and harvesting require substantially more human effort. Organic farming is especially labour-intensive due to bans on chemical herbicides. While conventional large-scale farms can simply spray pesticides, organic farmers must rely on manual labour for weed control. Although mechanical alternatives like cultivators and hoeing tools exist, they often lack the precision and efficiency needed, making weed management an expensive and time-consuming challenge. Even in conventional farming, stricter EU regulations on herbicides are likely to push farmers toward mechanical weed control, further increasing labour demands (Expert Interviews, 2025).

'Organic farming takes almost twice as many workers because a lot of tasks still can't be automated. While conventional farms use herbicides, we must harrow, hoe, and pull weeds by hand—so I end up going into the fields three, four, or even five times more often.'

- Expert Winklhofer

Farmers struggle to find individuals with both the technical know-how and the willingness to commit to farm work. This issue is worsened by seasonal fluctuations, which create unpredictable labour demands and make workforce stability difficult. Small-scale farms face financial constraints that hinder their ability to offer competitive wages, making jobs in industrial agriculture or other sectors more appealing. As a result, they often rely on family members, apprentices, or short-term workers, leading to inconsistencies in labour quality and productivity.

While automation and mechanisation could help address labour issues, their high costs and technical challenges keep them out of reach for many small-scale farms. This financial and technological hurdle maintains dependence on manual labour, continuing a cycle of heavy workloads and economic strain (Expert Interviews, 2025).

Demographic Changes

Farm demographics are a critical factor in understanding the structural changes in farming. Younger farmers typically manage larger farms, while smaller farms are often run by older farmers, sometimes beyond retirement age. When these farmers retire, their land is either abandoned or consolidated, increasing the average farm size (Rossi & EPRS, 2022).

The dominance of family-run farms (93% in the EU as of 2020) complicates farm exits, land-use changes, and intergenerational transfers (Eurostat, 2022). Farm exits are influenced by age, farm size, land prices, and retirement benefits (Corsi et al., 2021), with research showing that profitability and high agricultural prices reduce the likelihood of farmers leaving the sector (Breustedt & Glauben, 2007; Glauben et al., 2006). Larger farms and younger farmers are also less likely to exit (Glauben et al., 2006). Most new farmers enter through inheritance. Profitable farms encourage farmers to remain active until retirement, but without a successor, farms are often sold or merged, reducing overall farm numbers (Corsi et al., 2021). Expert interviews also highlight concerns about farm succession, particularly when children do not take over (Expert Interviews, 2025). Policy support reduces farm exits, with subsidies linked to lower exit rates (Glauben et al., 2006), yet current policies still favour large farms (see Appendix 7.3. Subsidies and Regulations).

Challenge 2 - Economic Viability

Economic viability presents its own challenge while also being influenced by the culmination of other structural issues. Small-scale farms experience significant pressure to stay profitable as they contend with rising costs, heightened competition, and the ongoing growth of industrialised agriculture (Czyżewski & Kryszak, 2023; Guth et al., 2022; Recanati et al., 2019; Satola et al., 2018). Their lower technical efficiency makes direct competition with large-scale operations nearly impossible.

This reality is supported by quantitative research: more than a third (34%) of surveyed farmers identified profitability maintenance as their primary challenge (see Figure 15). Major issues encompass rising costs, the shrinking price difference between organic and conventional farming, and competition from leading retail chains (Quantitative Research, 2025).

Ultimately, economic viability determines farm survival. As small-scale farms struggle, many are forced to sell, leading to land consolidation and an ever-decreasing number of independent farms (see Chapter 2.1.3.1. The Decline of Small-Scale Farms). The result is a shift toward larger, more specialised agricultural enterprises, accelerating the adoption of advanced technologies and further deepening the divide between small-scale farms and industrial farms (Beckers et al., 2018; FAO, 2000).

Challenge 3 - Technology & Mechanisation

The rising labour requirements in small-scale, diversified farms are directly related to the hurdles of mechanisation and automation. Integrating advanced technologies into these operations can be challenging due to multiple constraints.

Survey data underscores the importance of this issue, revealing that 17% of participants view mechanisation and technology-related challenges as the primary barriers to their farm operations (see Figure 15). The struggle to effectively implement mechanisation compels many small-scale farms to depend on manual labour, intensifying economic strain and hindering long-term sustainability in a progressively technology-driven agricultural sector (Quantitative Research, 2025).

Cost

Expert interviews reveal that mechanisation is usually less economically feasible for small-scale farms compared to larger ones. The main obstacle is the substantial costs associated with purchasing and maintaining agricultural machinery, which are challenging to mitigate due to the lower production levels typical of small farms. Additionally, the varied cropping systems found on small farms complicate the efficient use of specialised equipment. Each crop might need different machinery, resulting in mechanisation becoming prohibitively costly, especially for farms that grow many varieties. In contrast, larger farms benefit from economies of scale by focusing on a limited selection of crops, which allows for more effective and economical use of machinery (Expert Interviews, 2025).

'Why should I spend money on expensive, maintenance-intensive equipment if I do not need it? ... If my field is only 30 meters long, I spend more time retooling the machinery than I would just work through it by hand.'

- Expert Mauk

Flexibility

Growing various plants on small plots and frequently changing crops requires advanced technology. Rigid systems are often impractical because they lack the flexibility to adapt quickly to the diverse needs of different crops, workflows, and field sizes. The time invested in reconfiguring equipment can outweigh the advantages, leading farmers to prefer manual labour or simpler mechanised techniques for their efficiency (Expert Interviews, 2025). Manual methods enable farmers to adjust quickly to changing soil conditions and planting patterns, making them a cost-effective and adaptable alternative to inflexible mechanised solutions. Consequently, many small-scale crop farming tasks still depend on manual labour or minimal mechanisation (Dhillon & Moncur, 2023).

'Using technology always requires compromises because it lacks flexibility. Your hands and mind, however, are the most adaptable tools, enabling what machines cannot.'

- Expert Mauk

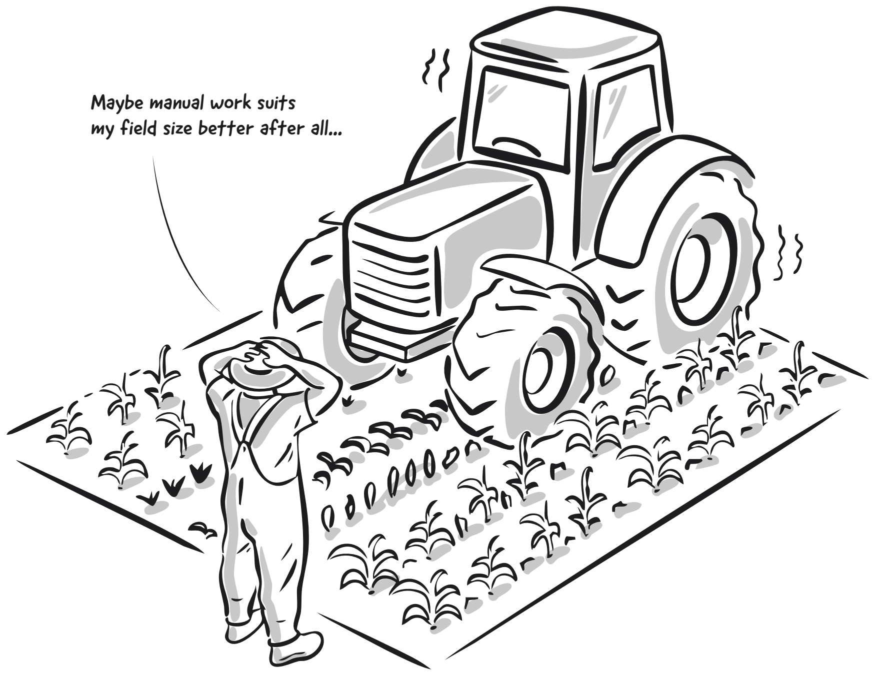


Figure 16: Illustration: The Challenge of Mechanization

Manoeuvring Space

Alongside costs, space limitations significantly hinder mechanisation on small farms. Both storage and field tasks necessitate adequate space for machinery to function effectively—this requirement is often not met on smaller plots. In contrast, large fields covering multiple hectares see minimal loss of area due to the need for turning and manoeuvring heavy machinery. Yet, on small farms, every square meter of arable land is crucial, making the land lost to machinery movement much more significant. Even compact machinery like narrow-track tractors and large single-axle vehicles still need several meters for turning, which further diminishes the land available for productive farming (Expert Interviews, 2025). Small, diversified farms like market gardens often favour manual or highly manoeuvrable equipment, such as two-wheel tractors (see Chapter 2.1.2.2. Mechanisation and Equipment) or wheel hoes, due to their ability to utilise available space more efficiently (Expert Interviews, 2025).

'With a single-axle machine, you might need 2 to 3 meters of headland. On foot, 1.5 meters is enough—just enough space to place a wheelbarrow. So, it is also a question of space.'

- Expert Mauk

Challenge 4 - Regulations & Bureaucracy

The demand for reporting in agriculture is increasing. To secure subsidies—essential for the survival of most farms in Europe, particularly small-scale operations—farmers must navigate extensive bureaucratic procedures. The transition to sustainable and diversified farming practices may further exacerbate administrative burdens, as compliance requirements, certification processes, and documentation for policy-driven agricultural initiatives become more complex (Ehlers et al., 2021).

Small-scale farmers face stringent and time-consuming regulatory requirements that hinder their operational efficiency (Babalola et al., 2023; Jouzi et al., 2017; SALSA Consortium, 2020). In Europe, the Common Agricultural Policy (CAP) represents the primary source of bureaucratic intervention in the agricultural sector. However, multiple reform attempts aimed at reducing administrative and financial burdens on farmers have largely failed (Howarth, 2000). One of the most recent initiatives in this regard is the Small Farmers Payment (see Appendix 7.3.4. Subsidies Targeted at Small-Scale Farms).

For example, certification procedures for organic and sustainable farming practices entail significant costs and paperwork, making compliance prohibitively expensive for many small-scale farms. Excessive bureaucracy not only discourages new entrants into the sector but also undermines the competitiveness of small-scale farms compared to large-scale agricultural enterprises. Reducing these administrative burdens is therefore crucial for fostering a more favourable regulatory environment for small-scale farmers (Aristovnik & Obadić, 2015).

The survey results highlight the burden of bureaucracy on small-scale farmers. 24% of respondents cited bureaucratic and regulatory requirements as their main challenge (see Figure 15). One participant summarised the issue:

> *'The time required for all the bureaucracy is far too great, leaving little room for truly valuable work.'*
> - Anonymous survey participant

Expert interviews underscored the difficulties that small-scale farms encounter due to complex subsidy systems that necessitate thorough documentation. Ensuring compliance requires considerable administrative oversight, which diverts time and resources away from essential farming operations. While environmental and safety regulations are intended to foster sustainability, they create disproportionate challenges for small-scale farms, which frequently lack the administrative resources to navigate these obligations. Furthermore, market regulations concerning direct sales and organic certification create additional hurdles, as small producers must adhere to strict standards that involve expensive inspections and extensive reporting. Although these regulations are designed to encourage sustainability and equitable practices, they often place small-scale farms at a disadvantage (Expert Interviews, 2025).

Challenge 5 - Market Access

Small-scale farms face systemic barriers to market access, as retailers and food processors favour larger suppliers (Guth et al., 2022; Satola et al., 2018). Price volatility, trade policies, and economic shocks multiply these challenges, fostering financial instability. Lacking economies of scale (Clough et al., 2020), small-scale farms struggle to compete, while administrative burdens and high transaction costs further limit their opportunities (Czyżewski & Kryszak, 2023).

Direct Marketing
Numerous small-scale farms utilise direct marketing strategies to navigate challenges. Insights from experts highlight that increased crop diversity enhances the importance of direct marketing, as farmers with a variety of crops are more inclined to adopt this strategy. A diverse product lineup enables them to cater to market demands and consumer preferences. On the other hand, wholesale markets typically necessitate specialisation in a limited number of crops, rendering them less suitable for organic mixed farms. While direct marketing provides flexibility in cultivation decisions, dependence on wholesale often leads to diminished crop diversity or monoculture for the sake of economic viability (Expert Interviews, 2025). This pattern is corroborated by the SALSA dataset, which reveals a notable correlation between crop diversification and engagement in direct marketing ($r = 0.234$, $p < .001$) (SALSA Consortium, 2020).

> *'The problem with wholesale is that you must specialise in two, three, or four crops instead of growing everything. But in direct marketing, it is the other way around because people are interested in your own products.'*
> - Expert Winklhofer

Direct marketing has its limitations. While diversification boosts resilience, it also increases logistical and promotional requirements. Moreover, inadequate infrastructure for local sales and distribution restricts its scalability, posing obstacles to consistent revenue generation. Respondents in the quantitative survey highlighted that attracting a sufficient number of customers for sustainable operations is a significant challenge. In contrast to large agribusinesses with robust supply chains, smaller farms dedicate considerable time and resources to establish a stable consumer base (Quantitative Research, 2025).

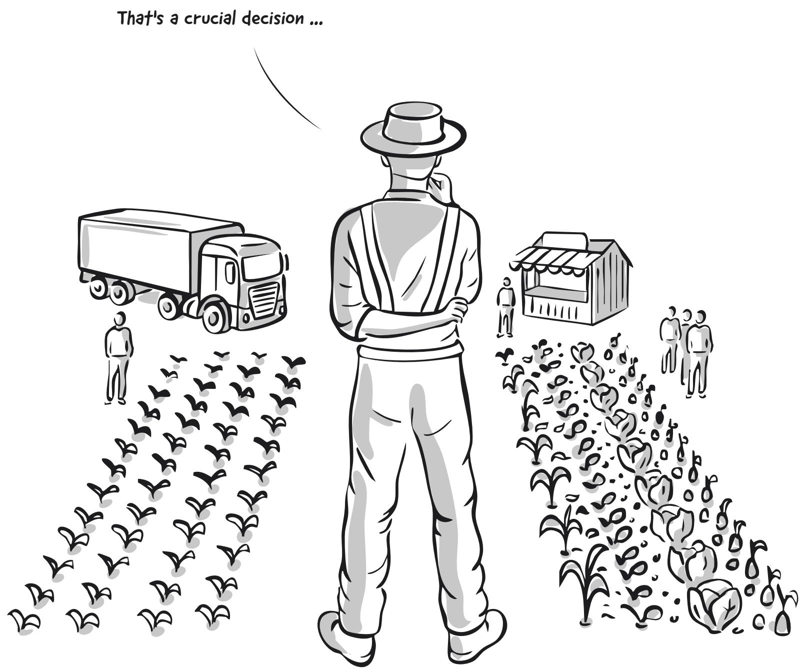


Figure 17: Illustration: The Importance of Direct Marketing

Challenge 6 - Climate & Environment

Agriculture is the most climate-dependent sector of the EU economy, making it particularly vulnerable to climate change. Climate-related changes are already significantly affecting agricultural production, and these impacts are expected to intensify. Small-scale farms, in particular, are disproportionately affected (Jacobs et al., 2019). Rising temperatures, changing precipitation patterns, extreme weather events (Cogato et al., 2019), soil degradation (Egidi et al., 2022), and the increasing spread of plant diseases and pests (Carozzi et al., 2022; Olesen et al., 2011; Roos et al., 2011) pose growing challenges.

Already, 15% of participants in a quantitative survey reported that climate change-related problems are their biggest challenges (see Figure 15), citing reasons such as crop failures due to pests, declining soil fertility, and extreme weather events (Quantitative Research, 2025)

Climate change is leading to increased rainfall in some European regions, raising the risk of flooding and storm damage, while other areas face prolonged droughts (Parmesan et al., 2014). Higher temperatures, particularly for crops such as wheat, contribute to yield losses (Jacobs et al., 2019). Shorter growth cycles due to warmer temperatures reduce the productivity of crops, as there is less time for biomass formation and yield development (Ciscar et al., 2019). Another consequence is the shift in plant phenology and flowering times, disrupting interactions between plants and pollinators, with negative effects on agricultural production (Jacobs et al., 2019; Shrestha et al., 2018).

The decline in soil fertility threatens food security, while increased sedimentation degrades water quality, and reduced water retention capacity heightens flood risks. Even now, soil degradation—partly due to unsustainable farming practices—is leading to declining soil fertility (Günal et al., 2015), which, in turn, drives climate change and results in biodiversity loss and decreased agricultural production (Keesstra et al., 2024). Organic matter is fundamental to soil health, influencing its structure, water cycling, carbon sequestration, and biodiversity, all of which are essential for sustainable agriculture (Czyżewski & Kryszak, 2023). Arid and semi-arid areas are particularly affected by ongoing desertification, further reducing the availability of arable land (Egidi et al., 2022). Additionally, competition for water resources between agriculture, industry, and households exacerbates the problem (Rocha et al., 2020). At the same time, extreme weather events such as storms and floods are becoming more frequent, destroying crops, livestock, and agricultural infrastructure (Cogato et al., 2019).

Climate change is expected to intensify pest and disease outbreaks due to rising temperatures and increased humidity, leading to more frequent and severe infestations. Additionally, it extends the active period of pests and plant pathogens, causing them to emerge earlier in the season, persist longer, and reproduce more rapidly, particularly in Central Europe (Olesen et al., 2011; Roos et al., 2011; Svobodová et al., 2013). The distribution of agricultural pests and diseases has already shifted as warmer temperatures and higher humidity create favourable conditions for their proliferation, resulting in significant crop yield losses (Skendžić et al., 2021). Currently, an estimated 20–40% of global crop production is lost annually due to pest and disease damage (Oliveira et al., 2021). Moreover, the dominant category of weeds (C3 species), which competes with crops for essential resources such as nutrients, water, and sunlight, is expected to benefit from elevated atmospheric CO_2 levels, further complicating weed management (Malhi et al., 2021).

Although climate change has some positive effects, such as longer growing seasons in northern Europe, the negative consequences far outweigh them. The combined impacts of temperature changes, precipitation patterns, and increased CO_2 concentrations affect crop yields differently across regions (Jacobs et al., 2019). Regional climate change impacts, vulnerabilities, and adaptation strategies are comprehensively analysed in the IPCC Fifth Assessment Report. For a more detailed analysis, see Parmesan et al. (2014).

Challenge 7 - Knowledge & Skills

Interviews and survey results revealed the necessity for new knowledge and the erosion of existing understanding during farm transitions. In the survey, 15% of respondents indicated (see Figure 15) that knowledge-related concerns, such as the loss of knowledge during transitions or a lack of new knowledge for sustainable practices, were their primary challenges. This observation is consistent with research highlighting an increasing need for new skills in response to evolving agricultural conditions (Dhillon & Moncur, 2023).

Acquiring and utilising new knowledge presents a substantial challenge in agriculture. Farming operations may struggle due to limited access to relevant information and a fear of changing strategies in light of shifting environmental conditions, stemming from the perceived risks associated with a lack of knowledge. The seasonal and long-term characteristics of most agricultural processes complicate the ability to see immediate cause-and-effect relationships, thereby hindering learning and adaptation. As one survey participant aptly noted:

> *'We learn so slowly because in farming each season lasts a whole year. It is not like baking bread, where you can test eight different methods in a single day.'*
>
> – Anonymous survey participant

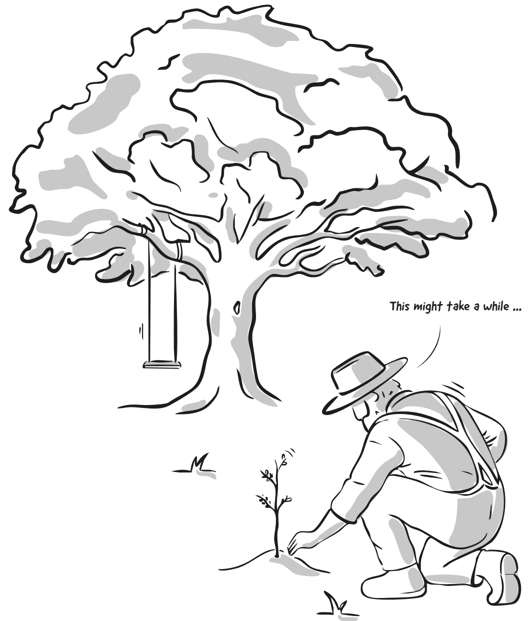


Figure 18: Illustration: Results Take Time to Emerge

Gaining new knowledge can be challenging, but losing existing knowledge is equally significant. Expert interviews have underscored this concern. Traditional knowledge loss during farm transitions or ownership changes remains a significant issue. Each agricultural region possesses distinct characteristics that textbooks often overlook. Knowledge specific to a site, such as soil types, crops, and management practices, especially concerning local variations, holds great value yet is frequently lost.

> *'Arable farming relies on a lot of knowledge, but much of it has been lost. We no longer have the grandparents who used to pass down their experiences about how these fields were managed. That knowledge is gone—it has disappeared with them.'*
>
> - Expert Fletschberger

A farmer with many years of experience on the same land usually knows their fields well. However, when a new tenant arrives after the farmer retires, this specific knowledge of the land must be meticulously rebuilt—a process that, as mentioned previously, demands a considerable time investment.

2.1.3.3. The Multifaceted Nature of the Challenges

In conclusion, small-scale farmers encounter numerous challenges that climate change intensifies. Because these problems are deeply intertwined, making essential adaptations is especially challenging and carries significant risk.

Additionally, farmers frequently navigate stringent regulatory frameworks due to their dependence on subsidies. Maintaining a farm is already difficult under typical circumstances. Therefore, it's understandable that many farmers are reluctant to make structural changes, given that these necessitate substantial financial investment and come with considerable risks, especially since the outcomes of such changes can take years to become evident. Moreover, the bureaucratic obstacles tied to these transitions further dissuade change.

Climate change increases the occurrence of pest infestations. A sustainable method to mitigate this issue is through crop diversification, which enhances pest resistance (Hatt et al., 2018; H. He et al., 2019; Murrell, 2017) and provides financial stability by offsetting losses from a single crop with earnings from another (Expert Interviews, 2025). However, diversification complicates mechanisation, leading to greater reliance on manual labour and exacerbating the current labour shortage. It also introduces bureaucratic hurdles and often necessitates direct marketing, which requires additional time and effort. Many farms remain dependent on subsidies for their viability, and changing their practices to improve pest resilience could jeopardise these subsidies, threatening farmers' financial stability. Therefore, addressing one problem may intensify other existing difficulties.

Agricultural consultant Urs Mauk effectively articulated this challenge in an expert interview:

'If I am 65 years old and plan to run my farm for only a few more years without a successor, would I really restructure everything on a large scale again? That comes with a lot of risk.

Farmers are often aware that their current system is far from perfect, but at least it still works well enough to survive. So why take the risk?

Should I put everything I have built up on the line for an uncertain future? ... An adjustment requires a complete overhaul of my system, which involves new knowledge, significant financial investments, and a high level of risk. Am I really doing this?"

- Expert Mauk

Understanding the intricate interconnections among these challenges requires a comprehensive perspective. The Systems Map created (see Figure 19) synthesises these insights into a comprehensive, systems-oriented schematic that instantaneously reveals the web of interdependencies. This visual, developed through integrating existing literature, expert interviews, and quantitative survey results, offers a conceptual framework addressing the main challenges faced by small farms and their relationships. Given the intricate and context-dependent nature of these issues, the graphic aims to avoid depicting fixed connections, instead emphasising broader patterns and dynamics. The specific interactions may vary according to the distinct characteristics of individual farming operations and diverse external influences.

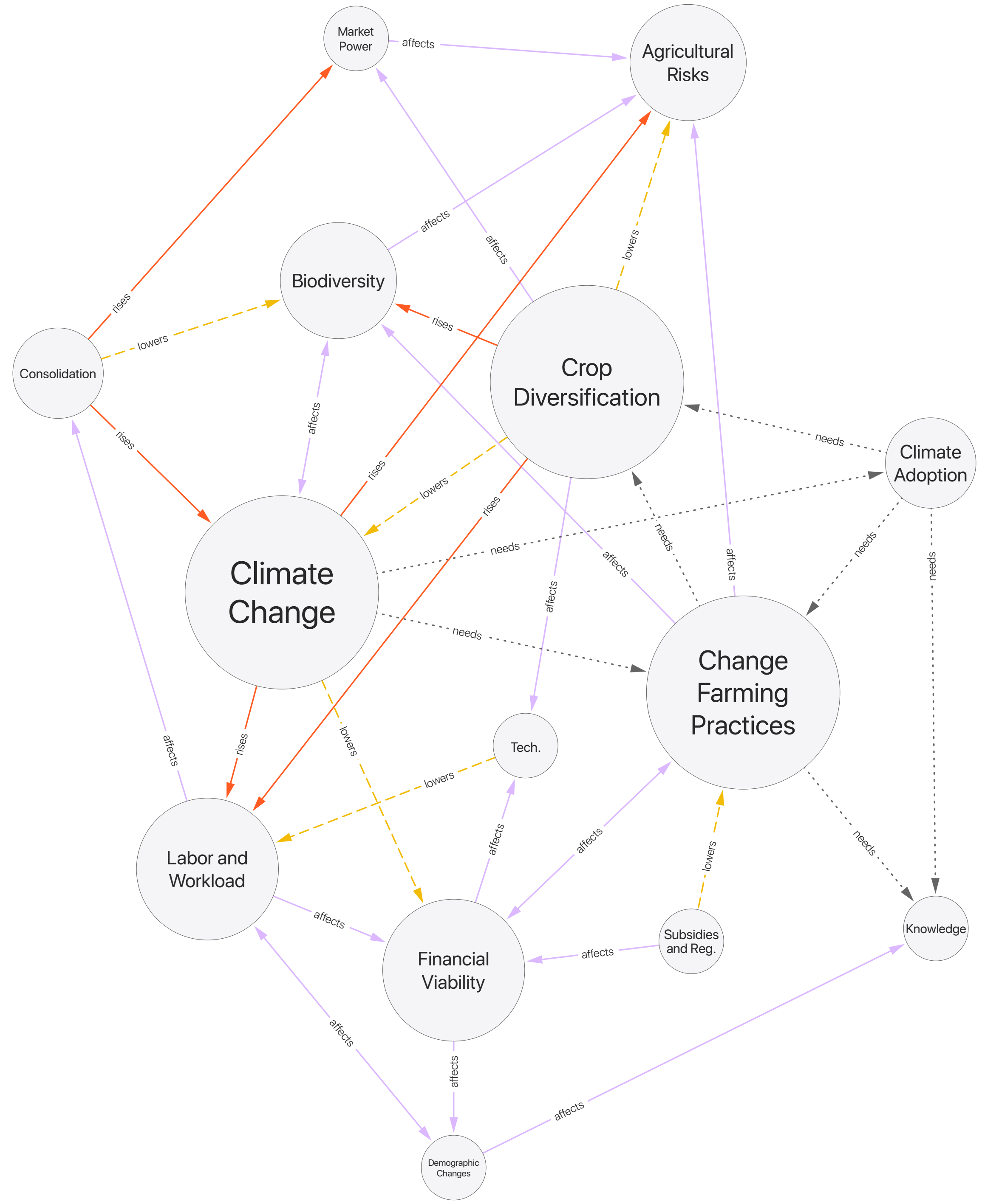


Figure 19: System Map Illustrating the Interconnected Nature of Challenges

Figure 20: Farmer with Beetroot (Gill, 2019)

2.1.4. Conclusion Agriculture

The first part of this research has thoroughly examined the structural dynamics of European agriculture, revealing that the future of small-scale farms stands at a crossroads. The rapid decline of small-scale farms is not merely a statistical trend but a profound transformation with far-reaching consequences.

Small-scale farms play a crucial role in creating a more resilient and fair food system. However, the challenges posed by climate change, biodiversity decline, and economic shifts are making their survival more uncertain. The loss of small-scale farms not only raises social issues but also significantly threatens agricultural sustainability and biodiversity. Yet, the dominant movement towards large-scale, efficiency-focused agriculture frequently undermines environmental resilience.

While the EU has started to recognise this issue, the prevailing subsidy model, which relies on per-hectare payments, still encourages farm consolidation. Although recent strategic plans of the CAP seek to bolster support for small-scale farms, their success is questionable, especially in light of the significant number of farm closures over the past decades. This prompts a crucial inquiry: Is this policy shift too late? Furthermore, depending on subsidies to artificially support small-scale farms is not a sustainable long-term solution. True sustainability requires a systemic transformation rather than dependence on financial aid.

Understanding why small-scale farms are struggling and how this trend might be reversed is essential for developing better strategies. Analysing the challenges these farms face reveals that they are caught in a web of problems (see Figure 19), which are only exacerbated by the ongoing impacts of climate change. Trapped in a network of dependencies and ill-suited technologies, it becomes difficult for farms to restructure themselves into an attractive alternative to large-scale agriculture.

Rather than relying on subsidies as temporary relief, what is required are targeted instruments that empower farmers to reclaim their role as both stewards and beneficiaries of the land. The symbiotic relationship between farmers and nature, where both thrive, is becoming increasingly difficult to maintain. With access to appropriate technologies and knowledge, small-scale farms can regain viability—whether through labour reduction, enhanced decision-making, or alternative agricultural models. The answer is not to prolong financial dependencies, but rather to empower farmers to autonomously and sustainably address these challenges. A farmer-first approach is essential, as those cultivating the land are best positioned to determine its needs.

This part of the research argues that the future of European agriculture depends on rethinking how we support small-scale farms. Innovations must be designed to accommodate the diverse realities of small-scale farms, rather than exclusively serving large-scale agribusiness.

Precision Agriculture Technologies (PATs) are frequently promoted as a remedy for this issue, yet it is still unclear whether these innovations genuinely deliver on their promises for small-scale farms. The upcoming chapters will evaluate the strengths and weaknesses of these strategies...

Figure 21: Autonomous field robot from Naïo Technologies (Naïo Technologies, 2021)

2.2. Precision Agriculture Technologies

Agricultural technologies are rapidly advancing toward a new paradigm known as Precision Agriculture Technologies (PATs), where digitalization, automation, and artificial intelligence (AI) play a central role in modern crop production (Santos Valle & Kienzle, 2020). Within this framework, Precision Agriculture has emerged as a transformative approach, utilizing advanced tools and techniques to enhance efficiency, productivity, and sustainability in farming. It encompasses a diverse range of innovative solutions, many of which have the potential to address key challenges faced by small-scale farmers.

While these technologies appear to offer significant advantages, their uptake remains quite limited, particularly among small farms. This chapter starts by defining the concept and different types of Precision Agriculture. It subsequently discusses the overall benefits of these methods, focusing especially on their potential impact for small-scale farmers, along with the reasons behind the low levels of adoption. The analysis also critically examines whether the introduction of such sophisticated technologies is a suitable or beneficial goal in this sector. Lastly, the chapter presents insights into how farmers view these technologies and their expectations regarding their application.

2.2.1. Introduction

2.2.1.1. Terminology

Agriculture, specifically large-scale agriculture, has seen a lot of technological advancements in the last few decades. This substantial transformation in agriculture was led by advancements in Precision Agriculture (Dhillon & Moncur, 2023). Precision Agriculture (PA) is an advanced farming practice that leverages technology to manage agricultural resources efficiently and sustainably (Mohammed & Munir, 2025). This concept is also commonly referred to as Precision Farming (PF), Precision Agriculture Technologies (PATs), Smart Farming, Agriculture 4.0, or Digital Farming (Karunathilake et al., 2023; Mohammed & Munir, 2025).

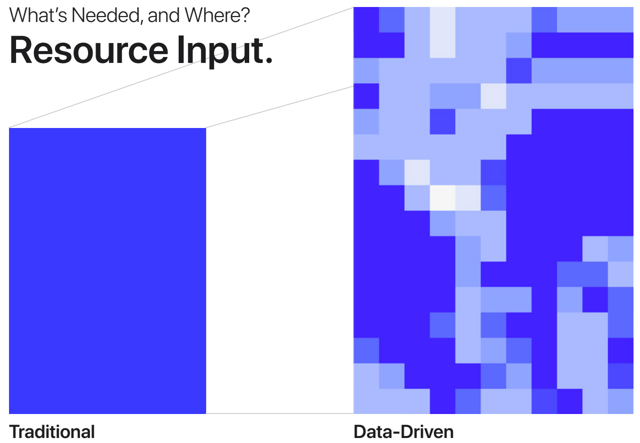


Figure 22: Illustration – Accounting for spatial variability within a field.

One of the earliest and most widely cited definitions of PA is provided by Pierce & Nowak (1999), who describe it as 'the application of farming strategies and methodologies to do the right thing, in the right place and at the right time', while data and technologies are used to detect and decide what is 'right' (Botta et al., 2022). A more recent and comprehensive definition, officially adopted in 2024 by the International Society for Precision Agriculture (ISPA), states that PA is 'a management strategy that gathers, processes and analyses temporal, spatial and individual plant and animal data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production' (ISPA, 2024). In simpler terms, PA aims to optimise the use of agricultural inputs (e.g., fertilisers, fuel) by accounting for spatial and temporal variability within the field (see Figure 22) (Iria et al., 2019).

The fundamental concept of Precision Agriculture —addressing the spatial and temporal variability of soil and crop factors within fields—is not a new idea. In fact, this principle has been practised for centuries. Before the mechanisation of agriculture, farmers cultivated small fields, allowing them to adjust treatments based on localised conditions manually. However, as field sizes increased and mechanisation advanced, it became more challenging to account for variability within a field and apply individualised treatments to different areas (Stafford, 2000).

PA extends beyond data collection, analysis, and site-specific input application. It also encompasses a wide range of technologies that automate field operations, including tractor auto-guidance systems and robotics for crop and livestock management (A. Balafoutis et al., 2017). The following section will discuss the five main categories of Precision Agriculture, which cover the key technologies and practices within this field.

2.2.1.2. Types of PATs

Since Precision Agriculture is a broad and multifaceted concept, the European Commission's Science and Knowledge Service has categorised Precision Agricultural Technologies (PATs) into three main types for policymaking purposes (Iria et al., 2019).

Guidance Technologies
Guidance technologies increase accuracy in agricultural tasks by employing GPS/GNSS-based auto-steering and navigation systems. These innovations enhance machine efficiency, decrease input overlap, and optimise essential activities like tillage, sowing, and fertilisation. By reducing human error, they aid in conserving resources and lowering fuel use. However, it's important to note that guidance technologies do not gather or analyse data; their main purpose is to enhance operational precision.

Recording Technologies
Recording technologies concentrate on collecting critical agricultural information, such as soil, crop, and climate conditions. This includes sensors (e.g., measuring moisture, temperature, and nutrient levels), UAVs for remote sensing, weather stations, and GPS-based yield mapping. While these technologies produce important raw data, they lack the ability to process or interpret it. To obtain actionable insights, integration with analysis or decision-support systems is necessary.

Reacting Technologies
Reacting technologies facilitate immediate modifications in agricultural inputs driven by collected data, improving resource efficiency and environmental sustainability. Examples include Variable Rate Application (VRA) for fertilizers and pesticides, intelligent irrigation systems, and automated spraying machinery. Although these tools markedly enhance precision in field interventions, they are not completely autonomous and still depend on human supervision—setting them apart from robotic systems.

While the European Commission's Science and Knowledge Service classifies PATs into the presented three main categories, A. T. Balafoutis et al. (2020) expanded this framework by adding Farm Management Information Systems (FMIS) and Robotic/Automation Systems. These two additional categories have gained significant attention in research, innovation, and market applications.

Farm Management Information Systems (FMIS)
Farm Management Information Systems integrate and analyse agricultural data to aid in farm planning and decision-making. This group encompasses Decision Support Systems (DSS), big data analytics, and farm planning tools that help optimise fertilisation, irrigation, pest control, and resource allocation. Unlike reactive technologies, FMIS do not carry out physical tasks in the field. Rather, they convert raw data into actionable insights, improving efficiency and informing long-term farm strategies.

Robotic/Automation Systems
Robotic and automation systems perform autonomous agricultural tasks with minimal human intervention, incorporating AI-driven tractors, robotic weeders, and automated harvesting machines. These advanced systems reduce manual labour by independently executing field operations based on recorded data and sensor feedback. Unlike reacting technologies, robotic systems go beyond adjusting inputs to fully automate actions, representing the most sophisticated level of smart farming by combining data collection, decision-making, and execution into a single system.

It is important to note that these five categories are not mutually exclusive. A particular PAT may simultaneously record and react to data. Robotic systems typically incorporate guidance technologies while also performing recording or reacting functions - or both.

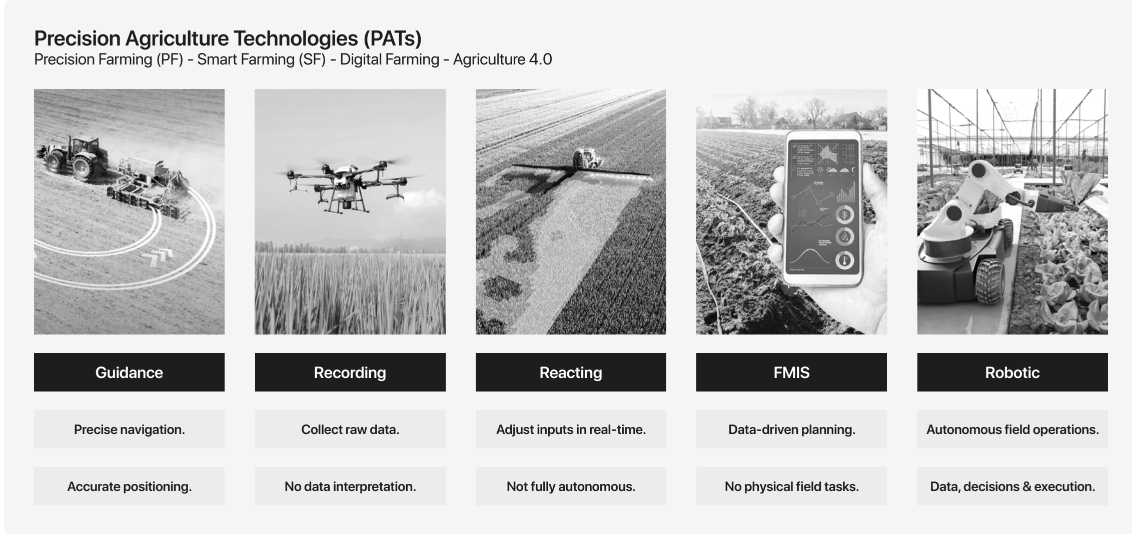


Figure 23: Types of Precision Agriculture Technologies

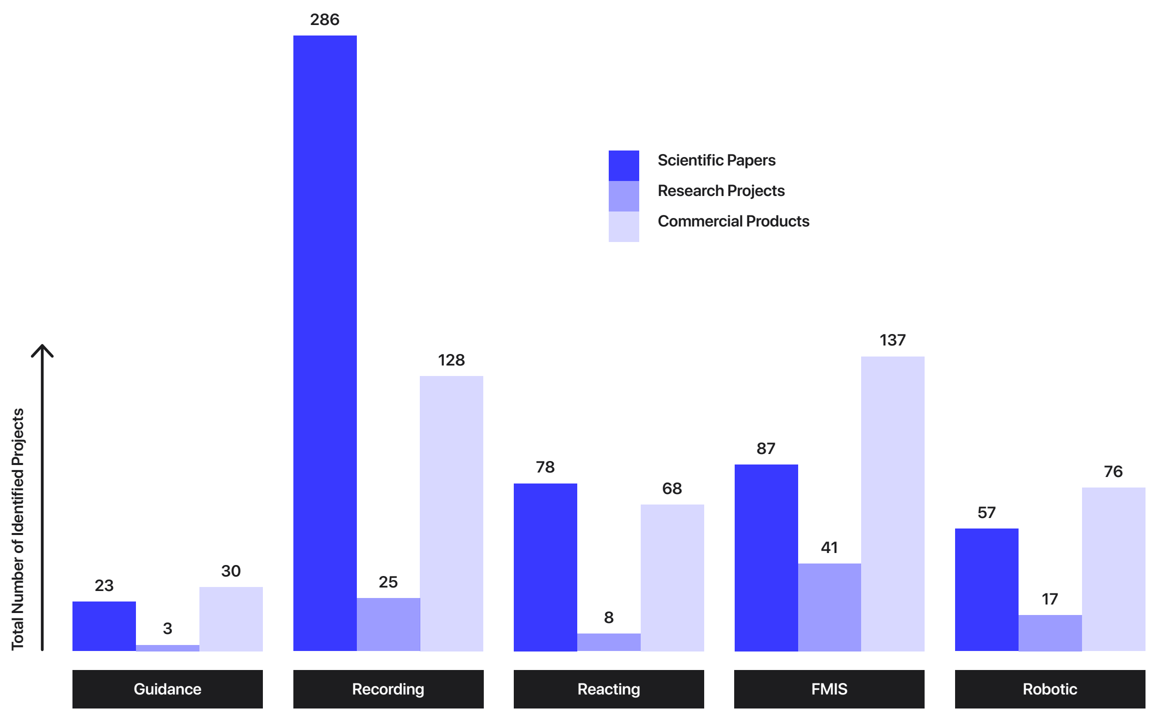


Figure 24: Allocation of Identified Smart Farming Technologies by Type (Recording, Reacting, Guiding, FMIS, Robotics/Automation); Created by the author based on (A. T. Balafoutis et al., 2020)

A. T. Balafoutis et al. (2020) also conducted an analysis of which types of PATs dominate scientific research, innovation projects, and commercial products (see Figure 24). Their findings reveal a strong emphasis on recording technologies in scientific papers, with significantly less focus on reacting technologies. This highlights a discrepancy in the field. Although data collection has advanced, the conversion of these measurements into practical applications on farms remains insufficient.

2.2.2.Benefits

This chapter explores the benefits of Precision Agriculture Technologies (PATs). It begins by outlining the general advantages of Precision Agriculture found in the literature. These benefits are then connected to the specific challenges faced by small-scale farms, as discussed in the previous chapter, to assess whether—and in what ways—these technologies can effectively address those challenges. In this manner, the chapter answers the following research questions:

RQ 2. *Why should small-scale farms adopt Precision Agriculture technologies?*

RQ 2.1. *What are the advantages of Precision Agriculture technologies in the context of small-scale farms?*

Precision Agriculture aims to enhance productivity, sustainability, and efficiency in farming operations (Mohammed & Munir, 2025). By improving the efficiency of both crop and livestock management, PA helps reduce resource consumption and operational costs (Monteiro et al., 2021). Through the systematic collection and analysis of soil, crop, and climate data, PA enables targeted interventions—whether performed manually or automatically—based on agro-climatic and economic models (A. T. Balafoutis et al., 2020; Rose & Chilvers, 2018).

2.2.2.1.Types of Benefits

While different scientific studies emphasise various advantages of PA, this section aims to provide a comprehensive overview by categorising its benefits systematically. The impact of PATs depends on the specific technology used. Some benefits are data-driven, leveraging real-time insights to optimise decision-making, while others are automation-driven, improving efficiency through mechanisation. These two categories are closely linked, as automation often relies on data, and automated processes are typically based on previously gathered insights.

This summary has been created from comprehensive literature research to enhance understanding. The list presents a structured outline of the benefits identified during the review. Each point will be elaborated on in the following sections.

Overview Data-Driven Benefits

Optimized Interventions & Resource Application

→ Reduced input costs through fewer, more targeted field interventions (manually or autonomously)
(Ahmad et al., 2024; A. T. Balafoutis et al., 2020; EPRS, 2016; Fabiani et al., 2020; Frauenhofer, n.d.; Karunathilake et al., 2023; Misara et al., 2022)

→ Reduced environmental impact by minimising chemical inputs and field interventions (VRT)
(Ahmad et al., 2024; A. T. Balafoutis et al., 2020; Bucci et al., 2018; Fabiani et al., 2020; Frauenhofer, n.d.; Meddeb et al., 2021; Misara et al., 2022; Mohammed & Munir, 2025; Navarro et al., 2020; Stafford, 2000)

→ Reduced labour demand through optimized, more targeted field interventions
(Akintuyi, 2024)

Enhanced Crop Management & Quality

→ Improved soil fertility through zone-specific nutrient management
(Ahmad et al., 2024; Fabiani et al., 2020)

→ Enhanced pest and disease prevention through data-enabled cropping strategies
(A. T. Balafoutis et al., 2020; Navarro et al., 2020)

→ Improved pest and disease detection (spotting) for timely, zone-specific interventions
(A. T. Balafoutis et al., 2020; EPRS, 2016; Frauenhofer, n.d.; Mohammed & Munir, 2025; Navarro et al., 2020)

→ Enhanced yield stability through timely interventions and Crop-Rotation Diversification
(Bowles et al., 2020)

→ More consistent product quality through uniform crop growth conditions
(A. T. Balafoutis et al., 2020; Mohammed & Munir, 2025)

Risk Forecasting and Strategic Planning

→ Enhanced risk management through predictive modelling (e.g., droughts, floods, pest outbreaks)
(Ahmad et al., 2024; A. T. Balafoutis et al., 2020; Mohammed & Munir, 2025)

→ Data-enabled cropping strategies for optimal crop selection, timing, and location
(Ahmad et al., 2024; Bucci et al., 2018; Karunathilake et al., 2023; Mohammed & Munir, 2025; van Klompenburg et al., 2020)

→ Accurate yield forecasting and climate-based planning
(EPRS, 2016; Meddeb et al., 2021; Mohammed & Munir, 2025)

→ Improved (climate) resilience by adapting cropping decisions to evolving field conditions
(Cravero et al., 2022; Jung et al., 2021)

→ Potential carbon credit earnings through easier access to climate-smart subsidies
(Pedersen et al., 2024; Raihan et al., 2024; Tripathi & Giri, 2024)

→ Reduced bureaucratic burden through automated data records for compliance and traceability
(Stafford, 2000; N. Zhang et al., 2002)

Overview Automation-Driven Benefits

Labour Reduction & Safety Improvements

→ Reduced labour demand through automated tasks (e.g. weeding)
(A. T. Balafoutis et al., 2020; EPRS, 2016)

→ Enhanced worker safety by reducing direct exposure to machinery and chemicals
(A. T. Balafoutis et al., 2020; Duckett et al., 2018)

Optimized Field Operations

→ Lower fuel consumption through minimized overlaps and optimized route planning
(A. T. Balafoutis et al., 2020; EPRS, 2016; Frauenhofer, n.d.; Monteiro et al., 2021)

→ Reduced soil compaction through optimized route planning and lightweight machinery
(EPRS, 2016; Frauenhofer, n.d.; Monteiro et al., 2021; Santos Valle & Kienzle, 2020)

→ Extended Operational Windows (earlier planting and later harvesting) in wet fields due to lightweight machinery
(Duckett et al., 2018; Grimstad et al., 2015; Xu & Li, 2022a, 2022b)

→ Minimized machinery wear and tear through data-driven operational efficiency
(EPRS, 2016; Frauenhofer, n.d.)

Explanation Data-Driven Benefits

Optimized Resource Use & Targeted Interventions

One of the most significant advantages of PATs is their ability to optimize resource use, particularly through Variable Rate Technology (VRT). This technology ensures that fertilizers, pesticides, and irrigation are applied only where necessary, reducing overall input costs and improving efficiency (Ahmad et al., 2024; A. T. Balafoutis et al., 2020; EPRS, 2016; Fabiani et al., 2020; Frauenhofer, n.d.; Karunathilake et al., 2023; Misara et al., 2022). By minimizing unnecessary chemical applications and excessive field operations, PATs also contribute to a lower environmental impact. Reduced input usage leads to less contamination of soil and water, while fewer trips across the field help mitigate soil compaction, preserving soil health over time (Ahmad et al., 2024; A. T. Balafoutis et al., 2020; Bucci et al., 2018; Fabiani et al., 2020; Frauenhofer, n.d.; Meddeb et al., 2021; Misara et al., 2022; Mohammed & Munir, 2025; Navarro et al., 2020; Stafford, 2000). Another crucial benefit of resource optimization is its impact on labour efficiency. With more targeted field interventions, farmers spend less time performing manual tasks, allowing for better workforce management, and reducing the need for physical labour (Akintuyi, 2024).

Enhanced Crop Management & Quality

PATs can improve soil fertility through zone-specific nutrient management, ensuring that the soil receives exactly what it needs in specific areas (Ahmad et al., 2024; Fabiani et al., 2020). Furthermore, early detection of disease outbreaks (Early Spotting) through sensor-based monitoring enables precise and localized treatment before infections or weeds spread across larger areas (A. T. Balafoutis et al., 2020; EPRS, 2016; Frauenhofer, n.d.; Mohammed & Munir, 2025; Navarro et al., 2020). This approach reduces the overall amount of inputs required, as treatment is applied only where necessary, while also minimizing labour time and yield loss. If stresses are detected early, suitable treatments can be applied to protect crops and prevent losses (Navarro et al., 2020; Neupane & Baysal-Gurel, 2021).

Early detection has two major advantages. First, diseases can often be identified before visible symptoms appear to the human eye, allowing for timely intervention. Second, continuous and seamless monitoring eliminates the risk of human errors, such as overlooking critical signs of disease (A. T. Balafoutis et al., 2020).

Additionally, intelligent and data-driven analyses enable the development of optimised cropping strategies, which enhance pest resistance by strategically combining plant species to create more resilient ecosystems (A. T. Balafoutis et al., 2020; Navarro et al., 2020). Moreover, data-driven input adjustments contribute to uniform crop growth conditions, ultimately leading to more consistent product quality (A. T. Balafoutis et al., 2020; Mohammed & Munir, 2025).

Risk Forecasting & Strategic Planning

Data-driven insights also enable enhanced risk management through predictive modelling. With real-time monitoring and predictive analytics, farmers can anticipate and mitigate risks before they cause significant damage (Eunice et al., 2022). This allows for more accurate forecasting of droughts, floods, and pest outbreaks, helping to identify patterns and adjust cropping strategies accordingly (Ahmad et al., 2024; A. T. Balafoutis et al., 2020; Mohammed & Munir, 2025). By leveraging data, farmers can develop optimised cropping strategies for better crop selection, timing, and field placement, leading to improved agricultural planning and resource efficiency (Ahmad et al., 2024; Bucci et al., 2018; Karunathilake et al., 2023; Mohammed & Munir, 2025).

Furthermore, climate resilience is enhanced by adapting cropping decisions to evolving field conditions, making agriculture more sustainable in the face of changing environmental factors (Cravero et al., 2022; Jung et al., 2021). Additionally, more accurate yield forecasting and climate-based planning help optimize resource allocation and improve long-term farm management strategies (EPRS, 2016; Meddeb et al., 2021; Mohammed & Munir, 2025; van Klompenburg et al., 2020).

Recording technologies also play a crucial role in reducing bureaucratic burdens for farmers, streamlining data collection and regulatory compliance (Ehlers et al., 2021). By automating compliance and traceability records, farmers can significantly decrease administrative workloads, ensuring seamless reporting and documentation (Stafford, 2000; N. Zhang et al., 2002). Moreover, access to climate-smart subsidies and potential carbon credit earnings becomes easier, as necessary data is already collected and readily available, eliminating the need for additional effort (Pedersen et al., 2024; Raihan et al., 2024; Tripathi & Giri, 2024).

Explanation Automation-Driven Benefits

Labour Reduction & Safety Improvements

Hiring and retaining agricultural workers has become increasingly difficult (see Chapter 2.1.3.2. Main Challenges of Small-Scale Farms), which is one of the key factors driving the rapid growth of field robotics over the past decade (Lowenberg-DeBoer et al., 2020). Automation significantly reduces labour demand by taking over repetitive and time-consuming tasks, such as weeding, which is one of the most labour-intensive activities in farming (A. T. Balafoutis et al., 2020; EPRS, 2016). Given the substantial time investment required for weed control, it is no surprise that weed control robots are among the most advanced agricultural robots to date (Fountas et al., 2020). At the same time, automation also contributes to improved worker safety by reducing direct exposure to heavy machinery and hazardous chemicals, making farming both safer and less physically demanding (A. T. Balafoutis et al., 2020; Duckett et al., 2018).

Optimized Field Operations

Automation also provides several practical advantages. One key benefit is lower fuel consumption, as optimized route planning reduces unnecessary overlaps and minimizes human errors, leading to more efficient field operations (A. T. Balafoutis et al., 2020; EPRS, 2016; Frauenhofer, n.d.; Monteiro et al., 2021). This increased efficiency also results in minimized machinery wear and tear, as data-driven operational strategies help extend the lifespan of equipment by reducing unnecessary usage and mechanical strain (EPRS, 2016; Frauenhofer, n.d.).

Another important advantage is reduced soil compaction. Optimized field routes ensure minimal overlaps, while autonomous vehicles can be designed to be lighter, further reducing the pressure exerted on the soil (EPRS, 2016; Frauenhofer, n.d.; Monteiro et al., 2021). The ability to construct lighter agricultural machinery also allows for extended operational windows, enabling earlier planting and later harvesting, even in wet field conditions, as lightweight machines can continue operating when heavier traditional equipment would get stuck or cause excessive soil damage (Duckett et al., 2018; Grimstad et al., 2015; Xu & Li, 2022b, 2022a). Extending the seeding and harvest windows is a key factor in improving farm profitability, and autonomous lightweight machines are well-suited to achieve this (Lowenberg-DeBoer et al., 2020).

Additional Benefit Identified in Expert Interviews

'Training the Eye'

One often overlooked advantage, emphasised in expert interviews but not extensively covered in literature, is how data collection aids in 'training the eye' and enhancing perception. Although current research recognises the knowledge-boosting effects of Precision Agriculture, it's important to view these benefits within a wider framework. Data-driven decision-making not only enhances field management but can also develop farmers' observational abilities over time. Data gathering can promote continuous learning and knowledge improvement by providing unbiased evaluations of field conditions and past decisions.

'When I see people leaving workshops thinking, ‚Ah, so that is how it works! All clear, great! How do we get started?' it's clear they still need someone—or an AI—to take them by the hand and guide them further.'

– Expert Mauk

Beyond immediate decision support, data collection and digital analysis hold considerable value during the early stages of farming or when transitioning to new agricultural practices, such as regenerative agriculture. These technologies can enhance farmers' comprehension of ecological relationships, assisting them in developing sound judgement. In this context, data acts as an educational tool, promoting both technical expertise and intuitive competence.

Ultimately, experts suggest that long-term success in agriculture is likely to depend more on enhancing knowledge and practical judgement than on indefinite reliance on technological aids.

'Every machine is just a crutch - something you might need for a while, maybe only at the beginning when you're trying something new and looking for reassurance. But eventually, you figure it out yourself and gain confidence in your own judgment.'

– Expert Bajohr

2.2.2.2. Opportunities for Small-Scale Farms

The numerous advantages outlined in the previous chapter demonstrate how diverse forms of PATs could help small-scale farms tackle their pressing challenges and lessen related burdens. They provide focused and practical solutions to a variety of main challenges faced by small farms (see Chapter 2.1.3.2. Main Challenges of Small-Scale Farms). By streamlining processes and improving field operations, these technologies can mitigate labour shortages and the demanding workloads typical in organic farms that depend on manual labour. Additionally, PATs enhance climate resilience through predictive modelling, data-driven crop planning, and reduced chemical use, which collectively promote healthier soils and more sustainable farming practices. Economically, they lead to lower input costs, improved resource efficiency, and stabilised yields - all vital for long-term viability. Regarding knowledge, PATs equip farmers with actionable, site-specific data that enables them to adapt and make well-informed decisions, even in the absence of traditional experience passed through generations. Although their impact on market access and regulatory challenges may be indirect, PATs still provide significant support by improving product consistency and automating compliance-related data collection, thereby streamlining certification and subsidy application processes.

While PATS are not a one-size-fits-all answer, they address many linked issues and show great potential for enhancing the resilience, efficiency, and sustainability of small-scale farming. However, their adoption rates are still relatively low. By 2016, only around 25% of farms in the European Union had adopted any form of precision agriculture (EPRS, 2016), encompassing all farm sizes and a range of technologies. Small-scale farms, in particular, exhibit a significantly lower adoption rate, with considerable differences across member states. For example, in Austria, just 6% of farms were using PATs in 2016 (ERDF, 2020).

This raises the important question of why small-scale farms are not adopting available PAT solutions more widely.

The following chapter examines the economic, technological, and social factors that hinder the adoption of Precision Agriculture technologies (PATs) among small-scale farms, answering the following research question:

RQ 3. *What are the key factors influencing the adoption of Precision Agriculture technologies among small-scale farms?*

2.2.3. Adoption Barriers

Despite the significant ecological and economic benefits of PATs, their adoption remains limited, particularly among small-scale farms (Buitkamp et al., 2021; Cui et al., 2018; John et al., 2023). While the PA industry has made considerable efforts to demonstrate the advantages of these innovations, surveys consistently indicate widespread reluctance (Paustian & Theuvsen, 2016). Large-scale farms tend to integrate PATs relatively quickly, whereas small-scale farms face greater complexities and inconsistencies in implementation (Barnes et al., 2019; John et al., 2023; Schimmelpfennig & Ebel, 2011).

This development is particularly concerning given the steady decline in the number of small-scale farms. Yet, Precision Agriculture presents an opportunity for these farms to maintain their competitiveness and position themselves as an economically viable alternative to large-scale operations (Al-Amin et al., 2022). However, the hesitant adoption of PATs prevents small-scale farms from fully benefiting from the potential economic and environmental advantages (Paustian & Theuvsen, 2016).

In the complex landscape of modern agriculture, the adoption of PATs among small-scale farms is influenced by a wide range of interrelated factors (John et al., 2023). Numerous studies have examined the key barriers and drivers shaping this process (Ammann et al., 2022; A. T. Balafoutis et al., 2020; Barnes et al., 2019; Hundal et al., 2023; Iria et al., 2019; John et al., 2023; Kernecker et al., 2020; Knierim et al., 2018; Marcus Pedersen et al., 2022; Pathak et al., 2019; Paustian & Theuvsen, 2016; Reichardt et al., 2009).

This chapter provides an overview of these critical influences by applying the conceptual framework proposed by John et al. (2023), categorising them into economic, technological, and social dimensions (see Figure 25).

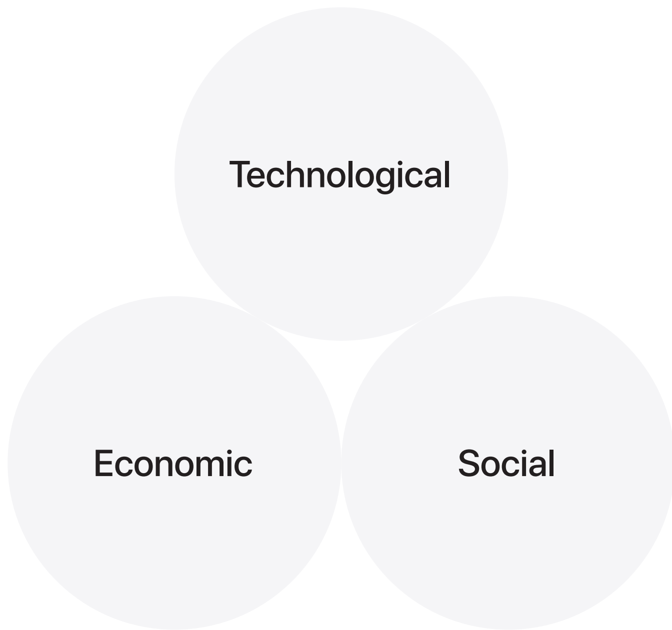


Figure 25: Categories of Adoption Barriers; Created by the author based on (John et al., 2023)

2.2.3.1. Economic Factors

As previously established, the economic survival of small-scale farms is already a significant challenge. The cost of PATs is often simply unaffordable for small-scale farmers (Dhillon & Moncur, 2023; Reichardt et al., 2009). The substantial upfront financial investment required to acquire advanced agricultural tools serves as a major barrier. However, even when farmers manage to overcome this initial cost hurdle, the issue of return on investment (ROI) comes into play. It is not just about the upfront expenses but also about carefully weighing the potential long-term benefits against these costs (Pathak et al., 2019).

Farmers must critically assess the economic advantages, such as increased crop yields and reduced input costs, against the capital-intensive nature of these technologies (John et al., 2023). Many express concerns over whether the eventual ROI will justify the initial expenditure, particularly when yields are already volatile, and profit margins are thin (Pathak et al., 2019). Limited cash flow and small profit margins make it difficult to absorb the financial risk associated with investing in new technologies (Paustian & Theuvsen, 2016).

Another ongoing financial challenge is the recurring costs of subscription fees and software licensing, which add to the overall financial burden (A. T. Balafoutis et al., 2020; Iria et al., 2019; Paustian & Theuvsen, 2016). Moreover, the cost of specialized technologies, such as GPS and Real-Time Kinematic (RTK) networks, tends to be disproportionately high on a per-hectare basis for smaller farms, further reinforcing risk-averse behaviour (A. T. Balafoutis et al., 2020). Additionally, limited access to credit or financing programs specifically designed to support technology adoption further constrains the ability of small-scale farmers to modernise through Precision Agriculture (Barnes et al., 2019; Iria et al., 2019).

The Common Agricultural Policy (CAP) seeks to address these financial barriers through targeted subsidies (see Appendix 7.3.3. Subsidies for Investment in Technology).

2.2.3.2. Technological Factors

Even basic mechanisation remains a challenge for many small-scale farms, as discussed in detail in a previous chapter (see Chapter 2.1.3.2. Main Challenges of Small-Scale Farms). Many well-established agricultural technologies are impractical for small-scale farms due to limited applicability (Dhillon & Moncur, 2023). Action-oriented technologies, such as agricultural robots, are typically designed for specific tasks (Lowenberg-DeBoer et al., 2020) and monoculture farming systems (Duckett et al., 2018). As a result, they are often unsuitable for small-scale farms, where only a small portion of tasks can be automated. A single-purpose robot provides little economic benefit if most farm work still relies on manual labour. The lack of adaptability to smaller farm structures remains a major barrier to adoption (Marcus Pedersen et al., 2022).

For large farms, action-oriented automation proves to be much more cost-effective. Technologies such as Variable Rate Technology (VRT) can greatly lower fertilizer expenses. For instance, on a 500-hectare farm, a 40% reduction in fertilizer use ensures a quick return on investment. Conversely, a small farm that achieves the same savings percentage on only one hectare sees little financial gain, complicating the justification for such an investment (Expert Interview, 2025).

According to expert Interviews, informing technologies, such as data-driven systems, face different challenges. Field robots solely collecting data offer too little immediate value for small-scale farms to justify the investment. Large-scale operations typically have the resources and expertise to analyse and apply such data effectively. Smaller farms often lack the time, technical expertise, or capacity to integrate data-driven insights into their workflows. The effort required to process and interpret the data frequently outweighs its potential benefits, making pure data-collection systems impractical for small and medium-sized farms. In an interview, expert Urs Mauk highlights this challenge:

'So, it [the robot] only collects data? No, a machine that only collects data might be worth it for large farms, but not for small and medium-sized ones. The added value of the data is too low, and the know-how to analyse and use it is lacking. If you are on a family farm, where everyone works 70 hours a week and isn't particularly tech-savvy, what are you supposed to do with even more abstract data?'

– Expert Mauk

This is especially true when the advantages of data-enhanced, optimised decision-making are not immediately visible or may take years to materialise. Unlike action-oriented solutions that provide tangible, short-term results, the connection between improved data-driven decisions and long-term farm performance is often unclear (Expert Interview, 2025).

2.2.3.3. Social Factors

Demographics
The influence of age and education on adopting PATs remains a topic of debate. Some researchers argue that younger and more educated farmers are more inclined to adopt new technologies. John et al. (2023) and Pathak et al. (2019) found that education enhances farmers' understanding of PATs, while younger individuals tend to be more open to innovation. Barnes et al. (2019) and Kernecker et al. (2020) further highlight that higher education improves data interpretation and decision-making, facilitating adoption.

However, other studies suggest that structural and financial factors are more decisive. Knierim et al. (2018) and Reichardt et al. (2009) found that farm size, costs, and technological complexity are more significant determinants than age or education. Similarly, Paustian & Theuvsen (2016) contend that although education can be advantageous, other factors have significantly stronger influences on adoption. Consequently, while age and education may affect adoption, their effects are frequently secondary to economic and structural conditions.

Cultural and Perception Barriers
Farmers' willingness to adopt Precision Agriculture is shaped not just by economic or technical factors but also by their mindset, experience, and social environment (Barnes et al., 2019; John et al., 2023). Many older farmers, for instance, rely on traditional methods and may see digital dashboards as unnecessary or even contradictory to their field-based intuition (Kernecker et al., 2020; Reichardt et al., 2009). Some worry that technology could mean losing independence, especially if it ties them to proprietary software (A. T. Balafoutis et al., 2020; Knierim et al., 2018). Others hesitate because data-driven farming feels overwhelming—it can seem like they need to relearn everything they already know (Iria et al., 2019; Paustian & Theuvsen, 2016). Even when some farmers succeed with new tools, adoption can remain slow if everyday challenges make knowledge-sharing difficult (Hundal et al., 2023; Pathak et al., 2019).

Technological Affinity
Implementing Precision Agriculture requires advanced technical skills, including sensor calibration and data analysis. However, access to specialised training remains limited for many small-scale farmers, creating a significant knowledge gap (John et al., 2023). This issue is further compounded by a lack of familiarity with geospatial and information technology tools, which contributes to reluctance and suboptimal use of available technologies (Kernecker et al., 2020). Farmers who have not previously engaged with data-driven platforms may find them challenging, particularly in the absence of intuitive user interfaces or peer support networks (Reichardt et al., 2009).

Advisory Services and Trust
For many farmers, adopting Precision Agriculture means depending on equipment dealers, software companies, or agribusinesses for training and support. However, these sources are not always neutral (John et al., 2023; Knierim et al., 2018). Some farmers worry that commercial advisors may push products that do not truly fit their farm's needs, eroding trust in these advisory channels (Barnes et al., 2019; Pathak et al., 2019). Peer learning—often a trusted method in farming communities—is not widely used in Precision Agriculture, largely because of the technical complexity involved (Iria et al., 2019; Kernecker et al., 2020). Without reliable, unbiased guidance, many farmers remain unsure whether investing in PA tools will genuinely improve their farm's productivity (Paustian & Theuvsen, 2016).

Alongside recognising the advantages of Precision Agriculture Technologies (PATs) and understanding the barriers to their adoption, it is essential to maintain a balanced perspective by examining potential downsides. This includes questioning whether universal adoption across all farms is truly necessary or appropriate. Insights from expert interviews reveal several frequently overlooked disadvantages of PATs, particularly in the context of small-scale farming. By addressing these findings, this chapter answers the following research question:

RQ 2.2. *What are the potential overlooked disadvantages of Precision Agriculture technologies in the context of small-scale farms?*

2.2.4. Drawbacks and Risks of Technology Adoption

The rise of PATs marks a significant shift in modern farming, driven by advancements in automation and data analytics. Beyond the various adoption barriers, an important consideration is whether overcoming these obstacles should be a priority to increase adoption rates. Given the previously outlined benefits, this may seem like a logical step. However, assessing the potential disadvantages of adopting these technologies is equally important. A thorough evaluation of PATs requires not only an examination of their advantages but also a critical analysis of their drawbacks.

While existing literature primarily highlights the benefits of PATs, expert interviews conducted in this study have also explored and analysed potential disadvantages. While techno-optimists champion these innovations for their potential to enhance sustainability and efficiency, techno-pessimists warn of unintended consequences, such as job displacement and increased reliance on proprietary systems. However, from the perspective of Don Ihde's postphenomenology—a framework that examines how technology mediates human experience—both views oversimplify the issue (Ihde, 2009).

2.2.4.1.Postphenomenology

Postphenomenology challenges the idea that technology is either a neutral tool or a simple extension of human intention. Instead, it argues that technology actively shapes human experience, amplifying certain aspects while diminishing others (Ihde, 2008).

Consider a farmer whose daily routines are reshaped by PATs. Traditional, hands-on knowledge—gained through years of manual fieldwork—is increasingly intertwined with data-driven insights. The rhythm of manual inspection and decision-making shifts to one guided by automated systems. This transition not only changes what farmers do but also how they experience their work (Verbeek, 2005).

Take precision farming robots, for example. Techno-optimists view them as tools that increase efficiency and sustainability by optimising resource use. Techno-pessimists, however, argue that these robots threaten traditional farming methods, foster dependency on proprietary technologies, and displace human labour. From a postphenomenological standpoint, these robots do more than enhance efficiency or disrupt labour markets—they actively reconfigure the farming process (Verbeek, 2005). Decision-making shifts from human judgment to algorithmic optimisation, with farmers relying more on technology providers and data-driven insights than traditional knowledge and intuition.

Multistability

A key concept in postphenomenology is multistability—the idea that technology does not have a single, fixed function but acquires different meanings based on context and user interaction (Ihde, 1990)This became evident in the analysis of expert interviews.

Farmer Winklhofer viewed the data-collecting robot as an extremely effective tool for minimising labour, thus removing the necessity for manual field inspections. In contrast, Farmer Fletschberger viewed it mainly as a form of control and a possible risk to data privacy, worried that farmers might become more reliant on data-driven decisions. Meanwhile, Farmer Bajohr viewed it as a knowledge generator, revealing links between soil quality, weather patterns, and yield forecasts, enhancing agricultural comprehension and supporting learning.

Each of these perspectives is rooted in the everyday experiences and concerns of the users. The robot remains unchanged as a physical entity, yet its significance is continuously reconfigured through interaction with diverse human practices and cultural contexts. This interpretation can also shift over time. The stability of a given technological function is not fixed, it evolves with cultural, social, or individual changes (Ihde, 2009). For example, while a farmer may initially use the robot only to determine the optimal location for planting potatoes, its role could expand as the technology becomes more established. Eventually, the robot could replace the farmer's knowledge entirely, making all field-related decisions autonomously.

Multistability undermines the idea that technology dictates a single, inevitable outcome. Instead, technologies interact with human intentions, cultural settings, and societal structures, allowing for diverse and often unpredictable applications. This challenges the techno-pessimist perspective, which assumes that technology determines human behaviour in a rigid, one-directional manner. Technology itself does not dictate its use—human choices do. Much like a knife can be used for cooking or as a weapon, PATs can be employed in different ways depending on human intentions.

However, even when farmers have control over how they utilise a tool, the tool itself structures the possibilities of what can be done. Farmers can use big data analytics to refine cropping strategies, amplifying data-driven insights, but at the same time, if they rely solely on automated reports, traditional, hands-on farming knowledge may be lost. This shift represents a fundamental reconfiguration of epistemic authority (Ferrario et al., 2023). Expertise moves away from experience-based knowledge toward data-driven analysis, creating a new dependency on technological systems. Therefore, PATs cannot be seen as neutral tools. They actively reshape agricultural practice, decision-making, and the role of the farmer. While they enhance efficiency, automation, and precision, they also diminish traditional knowledge, direct human observation, and alternative approaches.

The adoption of farm robotics and PATs is not merely a technical shift—it fundamentally transforms farmers' perceptions, workflows, and decision-making processes. A postphenomenological perspective highlights that these technologies are not passive instruments; they mediate human experience, introducing both benefits and challenges. Future developments in Precision Agriculture should not focus solely on technical efficiency. Instead, they must also consider how these technologies can be socially and epistemically integrated into existing farming practices. Only by acknowledging the complex ways in which technology reshapes human experience can we ensure that agricultural innovations serve both efficiency and the preservation of essential knowledge.

2.2.4.2. Critical Perspectives on Technology Implementation (Qualitative Research)

A lack of awareness regarding technology's active role in everyday life can lead to irresponsible design decisions. Don Ihde underscores that technology is never neutral; it shapes how we perceive and interact with the world, with its meaning emerging through use rather than being inherently fixed. Because technological outcomes are always shaped by human intentions, they remain open-ended rather than predetermined. Therefore, designers must consider possible negative effects and make careful choices to anticipate and reduce these impacts.

To enhance this approach, expert interviews were conducted to pinpoint the risks and potential disadvantages of adopting Precision Agriculture. The insights collected from these specialists provide an in-depth view of the challenges that need to be addressed during the design process. The next section outlines six significant risks identified, supported by direct interview quotes.

Risk 1 - The 'Shift in Epistemic Authority'

Data-Driven

The adoption of PATs is fundamentally reshaping epistemic authority in farming. This shift is often perceived as a risk, as expert interviews highlight the importance of maintaining farmer autonomy, which must remain unquestioned. Farmers insist on retaining full control over decisions regarding their land and strongly reject any form of external interference, whether it comes from political regulations, societal pressures, or technological advancements that limit their independence. This resistance also extends to data-driven technologies such as AI-powered field robots. While these innovations may be highly functional, they must be designed in a way that reinforces, rather than diminishes, farmers' decision-making power. Research consistently shows that farmers' ability to make independent choices about their land is a core principle. Any technology that threatens this principle is met with scepticism and resistance. An Expert highlights the frustration many farmers feel when external entities attempt to dictate their practices:

'And there is always someone standing there—socially or institutionally—constantly telling farmers what would be better and what they could do better ... I really see the danger that farmers might just quit and say, 'You know what? Then do it yourselves.''
– Expert Fletschberger

To ensure that PATs gain acceptance, farmers' expertise must remain central to the decision-making process. Technology should serve as an advisory tool, offering insights and recommendations while leaving the final judgment in the hands of the farmer. While farmers are open to innovations that support their decision-making, systems that function independently and impose rigid directives are perceived as intrusive. Even when AI-driven systems collect and analyse field data, they must not replace human judgment but rather guide a way that respects the farmer's role as the ultimate

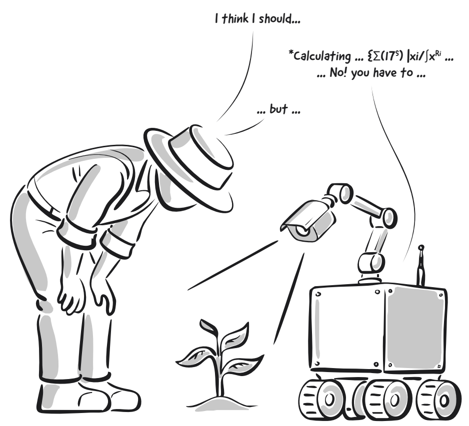


Figure 26: Illustration: The Final Decision Belongs to the Farmer

authority. This scepticism is rooted in the understanding that while AI can process vast amounts of data, it does not bear the consequences of its decisions—farmers do. An Expert articulates this concern, emphasising the need for AI to function as a supportive tool rather than an autonomous decision-maker:

'And later, the AI tells you how to manage your ecosystem [on the farm]. It can have advantages because it can collect data ... But on the other hand, what consequences does that have, and how does it restrict you?'
– Expert Bajohr

The central issue is responsibility. Farmers do not want to be dictated to by an AI system that does not take accountability for the outcomes. An Expert further explains:

'I do not want to be told by an AI, 'This is how you do it now,' because it does not take responsibility for the outcome—I do.'
– Expert Bajohr

Automation-Driven

While concerns about epistemic authority primarily arise in the context of data-driven decision-making, the automation of routine farming tasks is viewed differently. Farmers generally welcome automation when it takes over monotonous, labour-intensive tasks without interfering with their expertise. Robots that perform repetitive mechanical work, such as weeding or harvesting, are seen as valuable tools that alleviate workload pressures. Unlike AI-driven decision-making tools, which provoke fears of losing control, purely mechanical automation does not threaten farmers' autonomy.

However, scepticism arises when machines are not only automating tasks but also analysing data in ways that create the impression that they 'understand' the land better than the farmer. While AI-based decision-making tools raise concerns about control, automation introduces different anxieties, primarily about reliability. Farmers worry that even minor technical malfunctions could have catastrophic consequences for their yield and financial stability. An Expert highlights this fear, explaining how a small error, such as a two-centimetre deviation in fieldwork, could result in significant losses:

'If my colleague sends his autonomous robot out to the field at night, he cannot sleep ... If something—like the weed knives—shifts by just two centimetres, a lot can happen, and then his entire annual revenue is lost.'
– Expert Winklhofer

The reliability of automation is a major concern. An Expert questions whether these systems can truly function as intended:

'The question is, does it work? Or will it eventually mow everything down, without distinguishing between weeds and crops? You must be able to rely on these systems.'
– Expert Fletschberger

For automation to gain widespread acceptance, it must be equipped with robust safety mechanisms that detect and correct errors before severe damage occurs. Building trust in autonomous systems is a gradual process, requiring consistent and reliable performance. Farmers must feel confident that these systems will function as intended, without introducing new risks.

Figure 27: Illustration: Fear of an Automation Malfunction

Risk 2 - The 'Transparent Agriculture'

Surveillance

Automating compliance and traceability—highlighted earlier as a primary advantage of PATs—can greatly alleviate administrative burdens and enhance reporting efficiency. Furthermore, the pre-collection of agricultural data ensures easy access to climate-smart subsidies and carbon credits. Nonetheless, viewed from another angle, extensive data collection raises worries about creating an excessively transparent agricultural system. Numerous experts have expressed fears regarding this development in the interviews.

As farmers can use robotic systems to monitor their fields, there is a growing concern that regulatory bodies could also leverage this data for surveillance. Many farmers fear that extensive data collection may lead to increased reporting obligations and tighter government oversight. The scepticism surrounding surveillance, data collection, and the concept of 'transparent agriculture' reflects a more profound concern about losing control to state authorities or technological systems. A significant worry is that sharing agricultural data, or even future government mandates requiring such data, could result in greater regulatory interference. Farmers are concerned that this could lead to policy-driven interventions, additional restrictions, or even constraints on their farming decisions. Ultimately, there is a fear that these systems could contribute to establishing comprehensive surveillance mechanisms that would erode their autonomy. An Expert describes these concerns, emphasising how automated monitoring differs from traditional regulatory inspections:

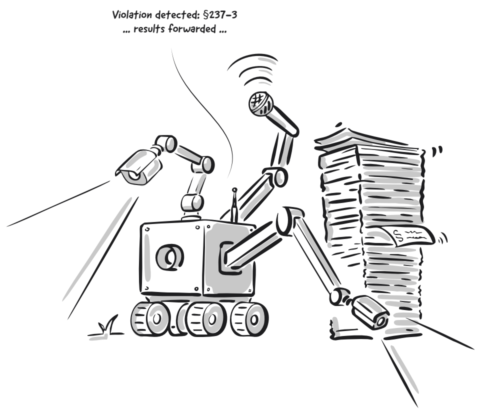


Figure 28: Illustration: Fear of Machine-Driven Surveillance

'Then a big issue is the surveillance topic ... We already have an enormous bureaucracy ... there's a control rate of 5%, and then someone [an inspector] comes around ... but that's different from knowing that my own equipment [e.g., field robots] is monitoring my operation 100% of the time—day and night—and every mistake shows up somewhere...'

– Expert Fletschberger

Data Ownership

These concerns are not limited to general field surveillance. Another issue raised is that as data collection becomes easier and more widespread, government agencies and funding institutions may increasingly expect access to this data. This could result in future subsidy programs being tied to the provision of specific data, forcing farmers to share detailed operational insights to qualify for financial support. Early developments in this direction are already visible, as some aspects of subsidy applications are now verified using satellite imagery. Many farmers are deeply uncomfortable with this trend, fearing that expanding data collection will primarily increase bureaucratic burdens rather than provide tangible benefits. An Expert highlights the growing unease surrounding satellite-based monitoring and its implications for farmers' autonomy:

'... but also, my own experiences, that now I am being monitored from above [Sentinel satellites]. It is not fun. ... So, we now must provide evidence that we are delivering results ... otherwise, they cut everything [subsidies], and they want to tighten it even more. ... You are constantly being observed, what you are doing in your field ...'

– Expert Bajohr

Similarly, another expert points to the increasing use of satellite imagery for regulatory enforcement, which fuels farmers' reluctance to embrace further data collection:

'It has not been that long since the authorities started working with satellite images. ... That means they are now looking, okay, what do you have in your application? ... And with the slightest violation of the rules, you get a penalty. Of course, that's why farmers are only somewhat keen on having more data collected about them, because exactly that can lead to bureaucrats tightening their control.'

– Expert Mauk

These concerns are valid. The European Parliamentary Research Service (EPRS), an independent body analysing EU policies, suggested this in a 2016 foresight study. The report stated that adopting PATs would make agriculture's environmental impact easily measurable and verifiable. Consequently, this could lead to policies that force farmers to use digital tools to collect more environmental data and share it with regulatory authorities (EPRS, 2016).

Given these concerns, it is critical to ensure that farmers retain data ownership. Farmers must have the right to decide who can access their field data and maintain complete control over its use. This data should primarily serve as an internal tool for farmers, helping them improve their operations, rather than becoming an instrument for government oversight or external control.

Risk 3 - The 'Dehumanisation of Agriculture'

The increasing reliance on data-driven agriculture raises concerns that farmers are becoming passive interpreters of algorithms rather than active participants in ecological stewardship. Land, once cultivated through intimate human connection, risks being reduced to a digital construct—quantified, analysed, and optimised exclusively for efficiency. While framed as progress, this technologisation may render agriculture sterile, eroding the intrinsic 'Farmer-Nature Symbiosis' that has long defined sustainable farming practices.

Figure 29: Illustration: Technology May Sterilize Farming

Expert interviews emphasise that the farmer's bond with nature is irreplaceable and essential for sustainable agriculture. This is especially true in organic farming, where intuition and direct observation are crucial. Farmers develop an instinctive understanding of their land, recognising subtle shifts in soil health, plant growth, and animal behaviour—something digital tools can measure but never fully replicate.

An expert underscores this, highlighting the value of firsthand observation:

'Because actually, if you are a good farmer ... two-thirds I can tell just by looking. Looking at the plants and seeing, oh, something is missing there ...'

– Expert Winklhofer

Another expert further stresses that field experience provides deeper insight than isolated digital readings:

'And my field experience definitely needs to be included somewhere as well, and I almost think it's worth more than any measurement at a single point because that only reflects that small point and not my entire system.'

– Expert Bajohr

Risk 4 - The 'Price of Progress'

'Google Maps Pitfall' - Cognitive dependency
While data collection and digital analysis can provide valuable insights, over-reliance on technology risks eroding fundamental agricultural skills and environmental awareness. On one hand, farmers can use collected data to deepen their understanding of their fields; on the other, excessive dependence on digital tools can lead to a gradual decline in traditional knowledge. Once central to agricultural expertise, essential practices such as observing soil conditions, weather patterns, or animal behaviour are increasingly outsourced to machines. As a result, the intuition and holistic understanding from firsthand experience may weaken.

Long-term reliance on data-driven systems reduces the ability to assess one's land independently. This loss is comparable to the widespread dependence on navigation systems like Google Maps—those who use them exclusively often lose their ability to orient themselves without digital assistance. Similarly, outsourcing agricultural decision-making to machines can diminish farmers' field intuition, creating a dangerous cycle in which technology, rather than experience, becomes the primary reference point. An expert warns of this risk, emphasizing the potential erosion of agricultural expertise:

'You can see that with an app that dictates everything, the farmer's knowledge and understanding of nature could be lost. ... I also see the danger that, if the machine takes over everything, this knowledge will be disrupted.'
– Expert Bajohr

This decline in experiential knowledge leads to new dependencies. Farmers become reliant on technology to understand their fields, an ability once cultivated through generations of experience. As with traditional map reading, which has largely faded in an era of GPS navigation, agricultural intuition risks being replaced by digital systems, making farmers increasingly vulnerable to technological failures. This detachment from direct experience, leads to a mediated relationship (Eisenstein, 2007) with the environment, where reliance on external systems creates distance rather than connection. Knowledge that is not actively used is lost.

Technological Lock-in - Technical dependency
While technological advancements increase efficiency, they also create long-term dependencies on specific providers, updates, and maintenance contracts. Highly specialized machines often lock farms into closed ecosystems, making it difficult to switch to alternative methods. This lack of flexibility can hinder adaptation to changing environmental and market conditions, restricting innovation and self-sufficiency. An expert explains how such dependencies discourage investment in new technologies:

'And that is why I will not invest in this machine anymore ... to get away from these dependencies. ... We might not be able to get these spare parts anymore because they simply are not being produced anymore. ...'
– Expert Bajohr

Overreliance on digital infrastructure creates new risks that could jeopardize farm operations. Many precision agriculture technologies (PATs) rely on GPS, sensors, and cloud services. If these systems fail - whether due to server outages, service terminations, or cyberattacks - farms may face severe disruptions. Problems that previously did not exist, such as GPS failures due to solar storms (Koebler, 2024), could suddenly halt operations. Power outages, connectivity problems, or software glitches may undermine crucial agricultural processes, leaving farmers with limited options. In the absence of analogue alternatives, such failures threaten entire harvests. An expert emphasises this growing vulnerability:

'... and you make yourself extremely dependent on all sorts of things. Can the company deliver what it promises? Is the internet connection stable? Are the updates working? If I work manually ... anything can happen, and I can just keep going.'
– Expert Mauk

Figure 30: Illustration: Technology Creates New Dependencies

Risk 5 - The 'Yield Optimiser'

In ecosystems, long-term success is not achieved through maximum resource exploitation but rather by maintaining balance. The interaction between soil, plants, animals, and the environment must be managed sustainably. While short-term efficiency measures, such as intensive fertiliser use or chemical pesticides, can temporarily boost yields, they often come at the cost of ecological stability, leading to long-term damage such as soil degradation and loss of biodiversity. A truly sustainable system is one that regenerates itself, providing more stable and reliable yields over time.

However, increased data-driven insights do not automatically lead to sustainability. Variable Rate Technology (VRT)—a Precision Agriculture tool that optimises input distribution—serves as a prime example. While often highlighted in the literature as one of the most significant benefits of PATs, its application depends entirely on human intent. It can be used to minimise inputs, protect ecosystems, and maintain stable yields, or it can be leveraged to maximise short-term production at the cost of environmental health. Technology itself does not dictate its use—human choices do (see Chapter 2.2.4.1. Postphenomenology). An expert illustrates this contrast, explaining how the same technology can lead to vastly different agricultural practices:

'And conventional agriculture can use it [Data-driven Technologies] and then it recommends: deep ploughing, heavy NPK [fertilizer] application, and spraying tomorrow. Or it says: balance the soil, use shallow tillage, and plant a cover crop. These are different interpretations of the same data.'
– Expert Mauk

Risk 6 - The 'Sustainability Bias'

While precision technologies, such as targeted pesticide use, can reduce environmental impact, they often function as course corrections within a flawed system rather than addressing the root causes of agricultural challenges. For example, PATs can help minimise pesticide application—a positive step in itself—but this can also create a false sense of progress, leading farmers to overlook more fundamental solutions, such as crop diversification or eliminating pesticide dependence. Without a holistic approach, technology risks reinforcing existing inefficiencies rather than transforming agriculture into a truly sustainable system.

True effectiveness in agriculture comes from prioritising natural processes over short-term efficiency gains dictated by industrial farming models. Long-term resilience is built through system-wide improvements, such as enhancing soil health and biodiversity, rather than optimising isolated factors at the expense of ecological stability. If sustainability efforts remain narrowly focused on incremental efficiency gains, they may only prolong the inevitable collapse of a system that is already under strain. An expert warns that while precision technologies may delay the consequences of unsustainable practices, they do not fundamentally solve the problem:

'With precision technologies, the [regeneration and recovery of nature] have indeed been further improved, but in the wrong direction. ... Maybe death takes longer, but you will definitely go over the cliff because you've ruined your entire system. ... For the past ten or twenty years, it has been clear that yields can no longer be increased, no matter what measures are taken.'
– Expert Bajohr

2.2.5.Perspectives on PATs of Farmers (Quantitative Survey)

Along with the previously outlined benefits, adoption barriers, and identified risks, it's essential to consider the views of the most impacted group: the farmers. Their insights are crucial for making informed and customised design decisions.

To investigate farmers' perspectives on precision agriculture technologies (PATs), a specific segment of the quantitative online survey was aimed at this. The findings here are derived from responses provided by farmers (n=44) from Austria, the Netherlands, and Germany. (Further details about participant demographics and the methodology can be found in Chapter 1.3.2. Quantitative Empirical Research (Online Questionnaire)). Demographic factors influencing response patterns are discussed only when statistically significant effects are noted. This portion of the research answers the following research questions:

RQ 3.1. *What is the role of Human-Robot Interaction (HRI) in the adoption of Precision Agriculture technologies?*

RQ 3.2. *What strategies can be implemented to enhance trust in Precision Agriculture technologies among small-scale farmers?*

2.2.5.1.General Perception

When asked about their overall perception of precision agriculture technologies (PATs) most participants (54%) showed a favourable attitude on a five-point Likert scale, with 22% indicating a very positive view (see Figure 31). However, it's vital to mention that this question was posed without further context, potentially leading to some level of response bias.

'How do you perceive precision agriculture and technologies like field robots?'

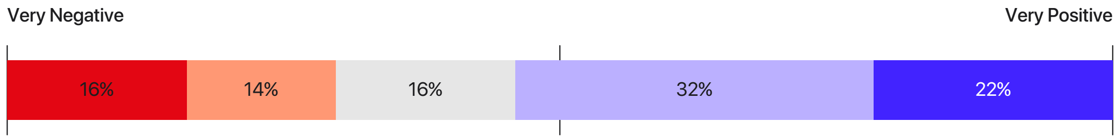


Figure 31: Quantitative Research (n=44); General Perception of PATs

To further explore initial associations with technological advancements in agriculture, participants were presented with an open-ended question asking what first comes to mind when thinking of technological developments and future technologies such as precision farming, robotics, and similar innovations in agriculture.

Precision agriculture provokes mixed feelings among farmers, balancing hope with doubt. While many see its promise, the steep costs pose a significant barrier. Respondents voice worries that upfront investments and ongoing maintenance might not yield sufficient financial returns, especially for smaller operations. Dependence on external vendors for repairs and data management fosters concerns about financial reliance on tech companies. Some farmers noted that heightened automation could erode their bond with nature and traditional farming practices, replacing instinct and hands-on expertise. Although larger, flatter farms may benefit from precision agriculture, smaller farms with varied terrains question its practicality, particularly in areas with poor GPS signals. Some farmers are apprehensive about a future overly reliant on machinery, fearing a shift toward industrial-style food production. Still, others might reconsider precision agriculture if costs were to decrease. In essence, these responses highlight a tension between the efficiencies brought by new technologies and the economic, philosophical, and practical challenges that obstruct broader adoption.

To better represent the open-text responses, they were organised into thematic categories and visualised as a word cloud (see Figure 32). Each response's sentiment- positive, negative, or neutral- was also assessed. For this, the complete written answer from each participant, along with their Likert rating regarding the overall perception of PATs, was taken into account for interpreting and categorising each individual response, enabling a more contextual analysis.

The analysis revealed that negative 'first thoughts' dominated at 60%, primarily due to concerns about cost. Additional worries involved the belief that technological solutions are unsuitable for small-scale farms and fears regarding increased dependency. On the other hand, the primary benefit noted was the anticipated decrease in workload. Notably, concepts like field monitoring and data-driven decision-making were rarely mentioned, with only one participant specifically mentioning 'supportive FMIS'.

'What are the first thoughts that come to mind when you think of technological developments and "future technologies" (e.g., precision farming, robotics, etc.) in agriculture?'

Figure 32: Quantitative Research (n=44); First Thoughts on PATs

A notable discrepancy emerged between the quantitative (Likert-scale rating) and qualitative (open-ended question) results from the questionnaire. While the Likert scale indicated a mostly positive perception of Precision Agriculture Technologies (PATs), the word cloud analysis of the open-ended answers showed a more critical or sceptical viewpoint. A closer look revealed that even those displaying strong enthusiasm on the Likert scale often utilised their open-ended responses to express significant concerns. Many acknowledged the potential benefits of PATs, such as reduced workload, but also pointed out challenges like high costs and limited relevance for small-scale farmers. This difference clarifies the considerable number of negative aspects noted in the qualitative analysis. Critical challenges were often mentioned first, even by respondents who rated PATs very positively on the Likert scale. This indicates that farmers are typically receptive to these technologies; however, the perceived drawbacks often overshadow the overall view.

'Could you see yourself investing in such technologies in the future?'

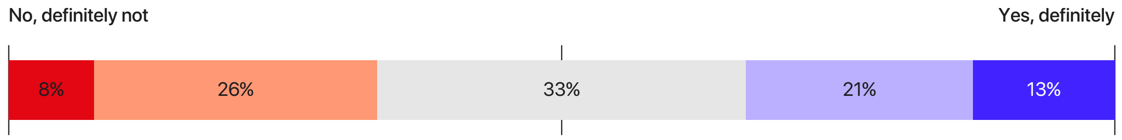


Figure 33: Quantitative Research (n=44); Likelihood of Investment

When participants (n=44) were surveyed about their potential investment in precision farming technologies, the results showed a fairly even distribution (see Figure 33). About one-third of respondents indicated they could not picture making such an investment, another third were unsure, while the last third demonstrated a definite interest in investing. Notably, just 8% said they absolutely could not see themselves investing in these technologies, even though 16% had previously rated them very negatively (see Figure 31).

2.2.5.1.Farmer-Robot Interaction (FRI)

In addition to grasping farmers' tangible expectations for functionality, designers need to understand their views on collaborating with robots. To investigate this, the questionnaire featured six statements evaluated on a Likert scale to measure agreement levels. The findings are shown in Figure 34.

The questionnaire responses indicate that most participating farmers have a generally positive view of robots in agriculture, though opinions vary significantly. A significant portion of respondents (70%) expressed that they can envision a robot as a beneficial partner on their farm, selecting either "agree somewhat" or "strongly agree." This suggests that many farmers are open to the concept of working alongside robotic systems.

When asked whether robots should be able to perform tasks independently and without supervision, responses were more divided. While 56% showed some degree of agreement, a notable portion (30%) expressed disagreement. This suggests that while some farmers are comfortable with robotic independence, others may be concerned about losing control or fully trusting automated systems. This also became evident in the expert interviews.

When asked about the potential effects of robotics on their personal relationship with work and nature, just over half of the respondents (53%) agreed that it would lead to change. Meanwhile, more than a third expressed disagreement. These responses indicate that many participants are reflecting not only on the practical functions of robots but also on the broader implications for their work experiences and surroundings.

The notion that robots might diminish the fulfilment of farm work garnered the least consensus. A total of 63% disagreed with this view, suggesting most participants do not link robotic support with a diminished sense of purpose in their jobs. Nevertheless, 23% voiced concerns, and another 15% stayed neutral, indicating that for some, the emotional or personal importance of farming influences their perspective on technological advancements.

Maintaining traditional working methods, despite the rise of robots, has sparked a range of opinions. Surprisingly, 45% of participants expressed opposition to this idea, while 40% remained neutral, showing some uncertainty, and only 16% agreed. This notable neutral stance might indicate that many recognise the value of tradition but also see the importance of balancing it with practicality and efficiency.

When asked if they are concerned about robots replacing their roles in agriculture, 55% of participants disagreed, while only 21% expressed agreement. This indicates that many do not see technology as an immediate threat. However, the neutral responses and some level of concern suggest that this issue might be more nuanced or context-dependent.

Overall, while the sample is relatively small and cannot be assumed to represent the broader farming population, these responses offer some insight into how this group of farmers thinks about robotics. Many seem open to technological support and even autonomy. Still, a number also reflect caution or uncertainty, particularly when it comes to the broader cultural and emotional dimensions of agricultural work.

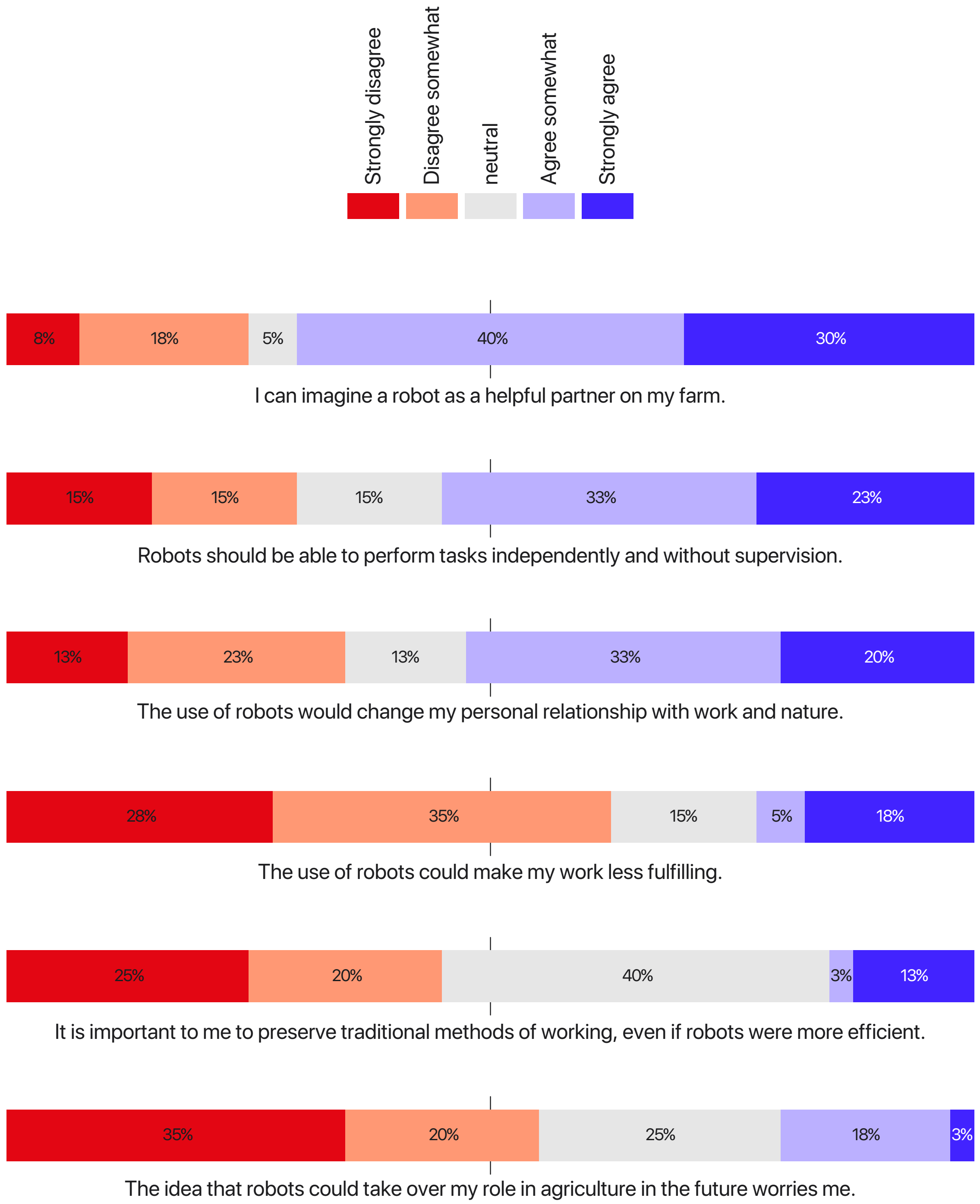


Figure 34: Quantitative Research (n=44); Farmer-Robot Interaction (FRI)

2.2.5.2. Expectations and Problem Areas

Expected Benefits

To better understand the specific benefits farmers associate with different types of technologies, they were asked to identify where they find data-driven technologies (e.g., field sensors and data collection tools) particularly helpful, and where they find automation-driven technologies (such as robots) particularly helpful.

To ensure comparability, the same multiple-choice question, with identical wording and the same eight answer options, was posed twice: once regarding data-driven technologies and once regarding automation-driven technologies. The responses are presented in a radar chart (see Figure 35), where each axis represents one of the answer options and shows the overall percentage of farmers who identified the respective technology as particularly helpful in that domain.

The results follow a largely intuitive pattern, yet several findings stand out. First, both technology types are widely perceived as beneficial: only 9% of respondents saw no relevant benefit from data-driven technologies, and just 7% said the same of automation-driven ones. Notably, robots are far more frequently associated with labour savings (68% of respondents), resource savings (59%), and efficiency gains (55%). This is somewhat surprising, as increasing efficiency, especially through targeted field interventions (see Chapter 2.2.2.1. Types of Benefits), is a core strength of data-driven technologies. These can also contribute to labour savings, a benefit currently seen almost exclusively as a function of automation-driven technologies (such as robots).

This aligns with insights from the expert interviews. Action-oriented solutions like harvesting robots provide immediate and concrete results. On the other hand, the link between enhanced data-driven decision-making and long-term farm performance is frequently seen as less straightforward or ambiguous (see Chapter 2.2.3.2. Technological Factors). Therefore, it is crucial to improve how the benefits of data collection are communicated to farmers. The cause-and-effect relationship between data-enhanced crop management and farm outcomes must be clearly illustrated to make its impact more tangible and convincing to farmers.

'In which areas do you consider the use of field sensors and data collection (data-driven) to be particularly helpful?'

'In which areas do you consider the use of robots (automation-driven) to be particularly helpful?'

Figure 35: Quantitative Research (n=44); Expected Benefits

Expected Features

When asked, "What features should a field robot have to be of interest to you?", farmers provided a relatively clear picture that closely aligns with the insights from the literature review and expert interviews. To effectively present the open-text responses, these were categorised into thematic areas and visualised in a word cloud (see Figure 36). The most mentioned topic was weed management, frequently cited as one of the most labour-intensive tasks, especially in organic farming.

Several other responses commonly referenced terms do not strictly qualify as "features" in a technical context. For instance, farmers consistently pointed out affordability as a vital consideration. While it may not be a feature in the traditional sense, its repeated acknowledgement implies that farmers associate affordability with functionality, perceiving economic accessibility as key to a robot's practical usefulness.

The strong focus on adaptability, independence, and cost-effectiveness highlights a distinct necessity for technology that can effortlessly fit into the varied realities of farm life. Farmers seek not highly specialised machinery but rather flexible systems that can execute various tasks across multiple crops, seasons, and terrains—all while being budget-friendly. Furthermore, the desire for robustness, reliability, low maintenance, and easy repairs showcases a practical understanding of rural environments: these machines must withstand tough conditions and be easy to service without complex, advanced infrastructure.

'What features should a field robot have to be of interest to you?'

Figure 36: Quantitative Research (n=44); Expected Features

Field-to-Field and Farm-to-Field Mobility

A crucial factor to consider in this context is transporting the device between different fields. Many farms have several distinct plots. The response to the question "Are there fields (plots) that are more remote or separated from your other fields?" reveals that most farmers (66%) noted that roads are necessary to access their fields. In contrast, 20% claimed their fields are within walking distance, while just 14% stated that all plots are directly connected. This indicates that the (ground-based) device needs to be either road-legal for travelling from the farm to the fields or sufficiently compact for easy transport between different plots.

'Are there fields (plots) that are more remote or separated from your other fields?'

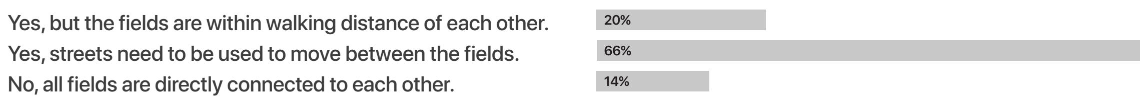


Figure 37: Quantitative Research (n=44); Field-to-Field Mobility

Problem Areas

The challenges outlined in the literature review and expert interviews (refer to Chapter 2.2.3, Adoption Barriers) were further evaluated through an online survey to identify which issues should be prioritised in the concept development phase. Farmers assessed the severity of each issue by answering the question: "How problematic do you consider the following aspects of precision agriculture?" with a slider that ranges from 0 (No problem) to 10 (Maximum problem). The results, displayed in Figure 38, show the average ratings from participants.

To ensure an impartial representation of the data, the median of the responses was selected, as it provides greater resilience to outliers. The figure highlights that the most significant challenges identified included costs (median = 9), dependence on technology (median = 8), and a lack of appropriate solutions (median = 7). Notably, while data privacy was emphasized in the expert interviews (see Chapter 2.2.4.2, Critical Perspectives on Technology Implementation (Qualitative Research)), farmers perceived it as a comparatively lower concern (median = 5).

'How problematic would you consider the following aspects of precision agriculture?'
(***Median values shown***)

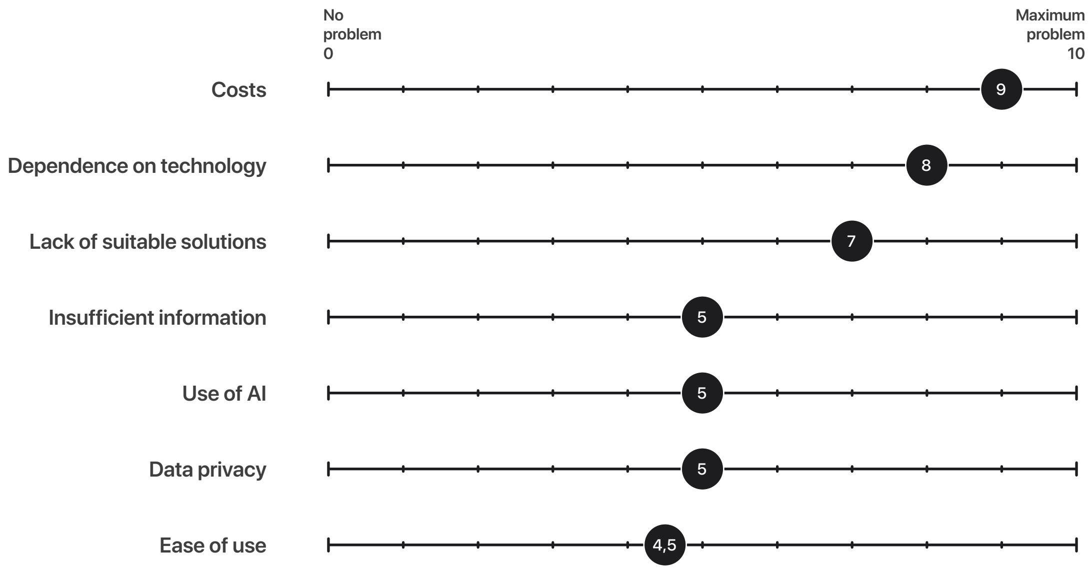


Figure 38: Quantitative Research (n=44); Ranking of Problem Areas

For the proposed concept, addressing cost and technological dependence is essential. The consequences of technological reliance were discussed in greater detail during expert interviews (see Chapter 2.2.4.2. Critical Perspectives on Technology Implementation (Qualitative Research)). Practically, this means the robot should be affordable and avoid creating new dependencies. Such dependencies might be cognitive or technical. Thus, the concept should incorporate a "manual override" feature, ensuring it remains functional even without internet or GPS access, which guarantees that the farmer is not left powerless in critical situations.

2.2.5.3. Status Quo - Data Practices and Decision Influence

To gain insights into the opportunities and obstacles presented by precision agriculture technologies (PATs) that are driven by data collection, it is crucial to investigate the existing practices of farmers in gathering data. This includes examining the types of data collected, the methods employed, and the extent to which this information impacts their daily decision-making processes.

Status Quo - Information Gathering Practices

The chart (see Figure 39) illustrates the responses to "How do you primarily collect field data?". It shows that 77% of respondents collect field data manually, making it the most common method. Laboratory analyses follow at 48%, while apps (30%) and on-site weather stations (27%) are moderately used. More advanced technologies like satellite images (20%), drones (9%), field sensors (5%), and autonomous machinery (5%) are used far less frequently.

In conclusion, manual and traditional methods still dominate field data collection, with digital and automated technologies playing a relatively minor role despite their potential.

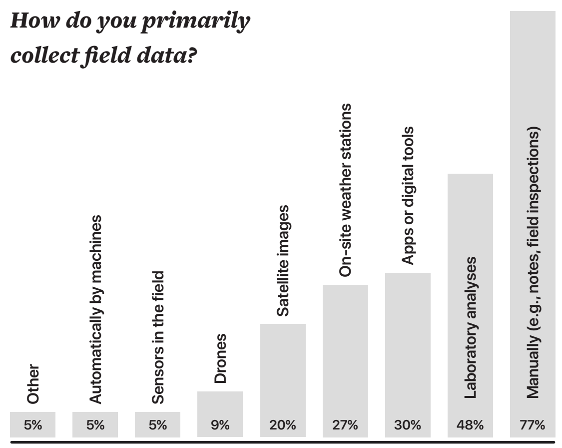


Figure 39: Quantitative Research (n=44); How Field Data is collected

Status Quo - Types of Information Collected

In addition to understanding farmers' data collection methods, it is crucial to recognise the specific types of data they gather. Commonly, farmers focus predominantly on harvested yields, which are recorded by about three-quarters of those surveyed (see Figure 40). Notably, there is more attention given to soil properties rather than on plant-related aspects like plant health and diseases. This is intriguing since expert interviews, including one with a biologist (Expert Interview, 2025), underscored the importance of gathering information on fungal and bacterial plant diseases. The concentration on soil data could be partly attributed to the readily available laboratory analyses, typically provided for soil samples.

Overall, it appears that the collection of plant-based data is an underexploited field with significant potential. Specifically, plant health indicators can provide immensely valuable insights, which are discussed in more detail in a later chapter (see Chapter 2.3.1.2. Field Phenotyping). Additionally, while biodiversity data and bioindicators hold substantial informational value, they rank among the least commonly gathered data types.

Expert interviews highlighted that effective data collection poses a significant challenge. A recurring theme was the lack of time and the perceived minimal benefits, which frequently discourage farmers from engaging in data collection efforts (Expert Interview, 2025). This viewpoint highlights the realistic limitations and motivational hurdles that hinder the broader use of data-driven methods in the field. One expert stated:

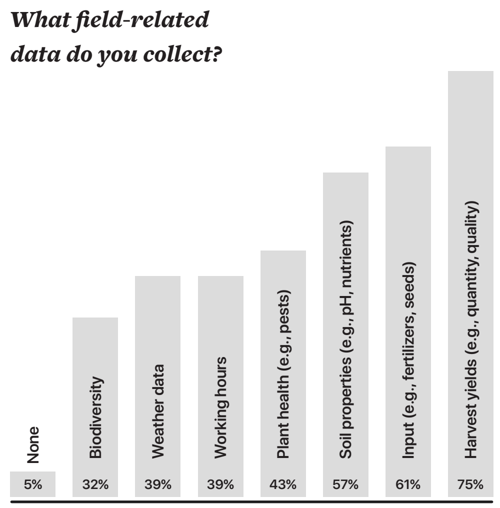


Figure 40: Quantitative Research (n=44); Type of Field Data collected

"... we have stressed farmers. They have no interest in data collection, and even less interest in data archiving and all that stuff."
- Expert Mella

Key Influencers and Influences in Decision-Making

The mere collection of specific data by farmers does not necessarily indicate its influence on their decision-making. To gain a deeper understanding of the reasoning behind their choices and the role data analysis plays in this context, farmers were asked: "How much influence do the following factors have on your field management decisions (e.g., seed selection, soil cultivation)?"

Responses were given on a scale from 0 (no influence) to 10 (maximum influence).

To ensure an unbiased representation of the results, the median was utilised due to its resilience against outliers. As illustrated in Figure 41, farmers place the greatest emphasis on their personal experience (median = 8), followed by peer interactions (median = 7.5) and professional advice (median = 7), which has an equally significant impact as environmental factors. Interestingly, the analysis of data is rated the lowest in terms of influence. This indicates that even when data is gathered, its impact on decision-making is limited - farmers tend to trust their personal experience and peer advice more.

***How much influence do the following factors have on your field management** (**e.g., seed selection, soil cultivation**)?*
(***Median values shown***)

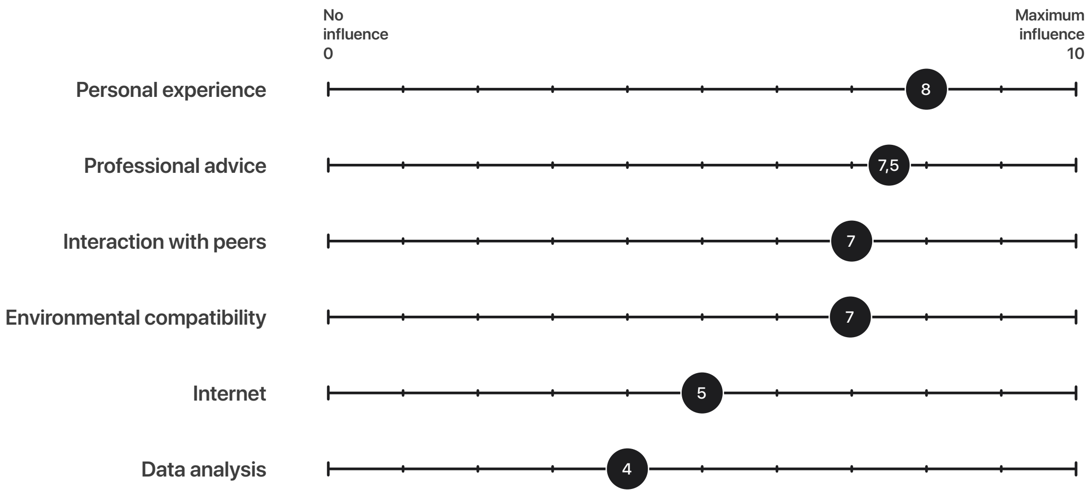


Figure 41: Quantitative Research (n=44); Ranking of Problem Areas

This conclusion aligns with findings from the literature review, indicating that peer learning - a strategy frequently adopted in farming communities - has not been widely applied to advanced technologies like data analysis, mainly due to the complexities involved (Iria et al., 2019; Kernecker et al., 2020) (see Chapter 2.2.3.3 Social Factors).

Peer-to-peer learning plays a crucial role. To successfully introduce and promote the adoption of new technologies, it's vital to establish a direct, farmer-led dialogue regarding the proposed design as part of a market entry strategy. Farmers should have the chance to share their experiences and insights, and ideally, they should have the option to borrow or lease components, such as sensors, from trusted peers, creating a more accessible entry point.

Renting and Sharing

This issue is closely related to farmers' general willingness to share or rent equipment. The online survey addressed this by asking: "Would you be willing to rent or share machines or equipment for fieldwork?" Respondents rated their willingness on a scale from 0 (Absolutely not) to 10 (Very willingly). As depicted in Figure 42, the results reveal a general openness among farmers to both options, with a slightly stronger preference for sharing (median = 7) compared to renting (median = 6).

Would you be willing to rent or share machines or equipment for fieldwork?
(***Median values shown***)

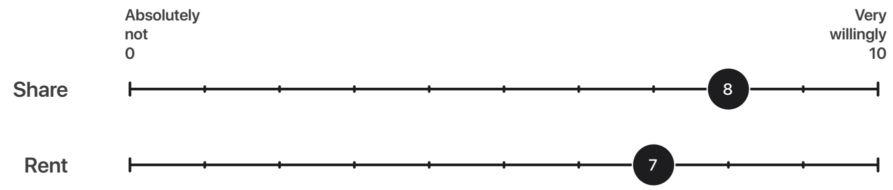


Figure 42: Quantitative Research (n=44); Ranking of Problem Areas

This topic also came up in expert interviews. There, it became clear that farmers' attitudes vary, but the potential is recognised, especially within small, local cooperatives. Fast access to equipment is crucial for time-sensitive tasks such as sowing or hoeing, which must often be done quickly depending on weather conditions (Expert Interview, 2025).

"Rental stations have grown significantly in recent years and decades, but I think there is still a lot of potential for growth... From an economic and agricultural perspective, it would be ideal if a farmer says, 'I only need my tractor twice a week, and it only runs for a few hours, so I'll rent it.' But this willingness is not strongly developed among many yet."
– Expert Fletschberger

For the envisioned concept, this implies that, in addition to sharing components, the optimal situation would involve promoting this sharing within regional cooperatives. Such organisations provide farmers with quick and flexible access to shared equipment. Conversely, external rental services may be inadequate for weather-sensitive tasks due to limited availability and possible delays.

Figure 43: Designer Engaging Farmers in Direct Design Discussions

2.2.5.4. Conclusion & Key Considerations for Designing PATs for Small-Scale Farms

It is essential to highlight the benefits of data collection in agriculture. Currently, data collection plays a minor role on many farms and, when it does occur, it is often done manually using handwritten notes. Significant untapped potential exists in assessing plant characteristics and biodiversity, but this aspect remains underrepresented. Unlike machines such as harvesting robots, where advantages are immediately visible, the cause-and-effect relationship between data-driven crop management and improved farm outcomes is often not recognised. Making this connection visible and understandable is key to helping farmers grasp its tangible value.

A market entry strategy must include direct, farmer-led conversations about the proposed design to successfully introduce and encourage the adoption of new technologies (see Figure 43). Farmers should be actively involved and encouraged to share their experiences and insights. While farmers do not rely heavily on gathered data, they are often influenced by the practices and successes of their peers.

Facilitating knowledge exchange among farmers, particularly regarding Precision Agriculture Technologies (PATs), is crucial for encouraging their adoption and ensuring long-term success. Ideally, PATs, or specific elements like sensors and modules, should be designed for sharing or rental among trusted peers. Peer learning stands out as one of the most effective yet underutilised methods for promoting new technologies, as farmers often trust insights from fellow farmers more than those from external sources. A modular design with a peer-to-peer learning approach provides a low-barrier entry point, building trust while supporting gradual adoption. It also helps alleviate the substantial challenge of high upfront investments, a primary obstacle to adoption. Research indicates that farmers are receptive to sharing and rental models, especially in local cooperatives.

In addition to building trust through peers, the design must incorporate a "manual override" feature to further enhance trust in the technology itself, as the fear of overdependence on technology is ever-present. This would ensure that the system remains operable even without internet or GPS access, giving farmers control during critical moments and fostering trust in the technology.

Regarding functionality, the design must be highly flexible and capable of supporting various tasks. A significant barrier to adoption is the lack of suitable solutions for small-scale farms. Farmers are not looking for highly specialised machines, but for versatile systems that can perform multiple functions across different crops. One of the key functionalities farmers expect is support in weed management, which they consistently cite as a top priority.

In addition to task flexibility, the system must also be location-flexible. It should either be road-legal for travel between fields and farms or compact enough for easy transport across plots.

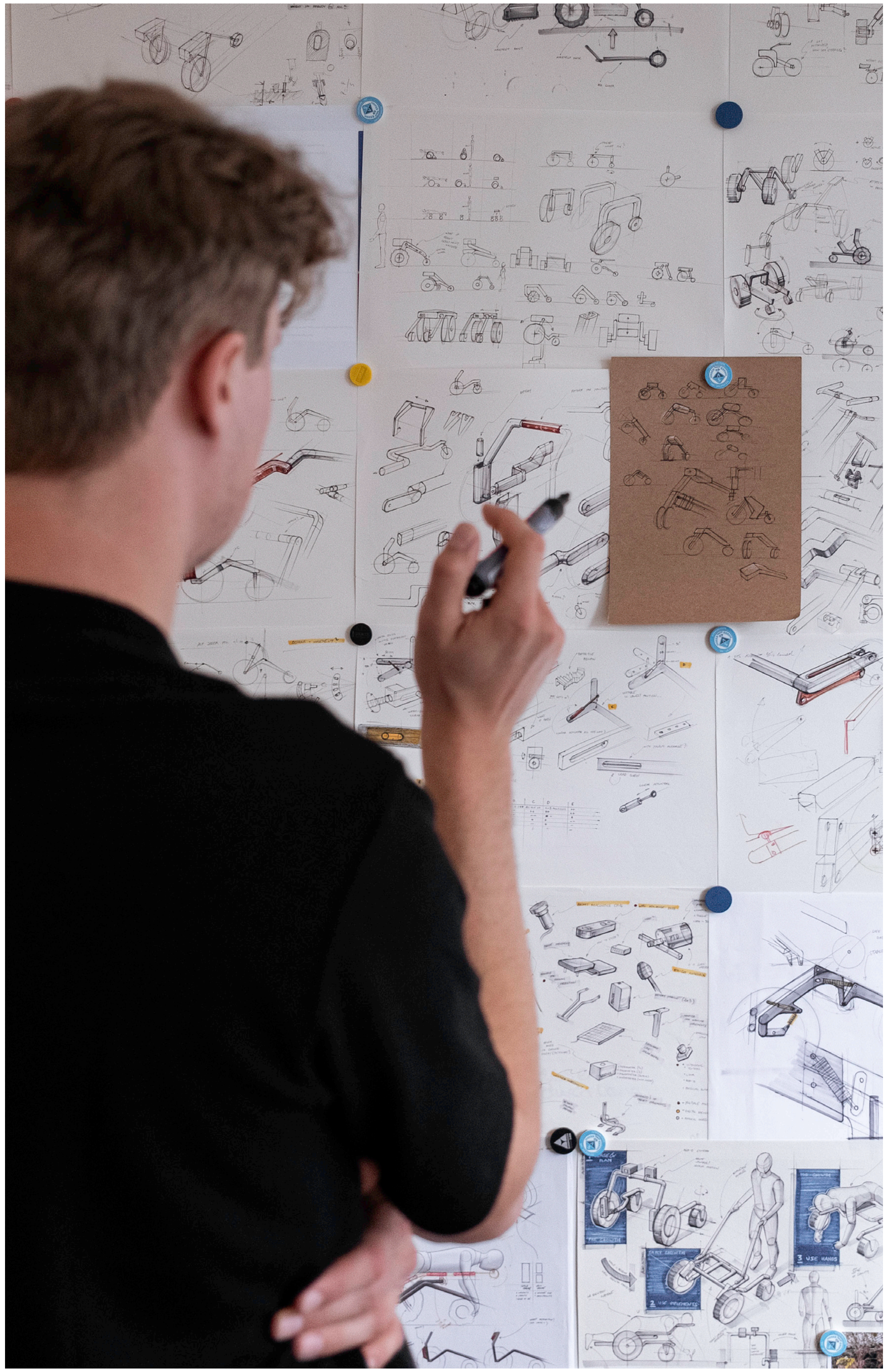


Figure 44: Interwoven Approaches to Design and Technology Research

2.3. Technology Choices in Design

Understanding the emerging technologies that drive Precision Agriculture is crucial for creating tools suited to farmers' requirements. This chapter provides an overview of these technologies, serving as a basis for crucial design and technology choices within the proposed concept. It facilitates informed decision-making throughout the entire design journey. Although this chapter is a segment of the broader research initiative, it is regarded as distinct from the main research area since the insights shared here were developed alongside — and intricately woven into — the design process (see Figure 44).

According to Xu & Li (2022b), a typical field robot consists of five essential components: a mobile platform, sensors for both phenotyping and navigation, computing units for data processing and control, and manipulators (see Figure 45).

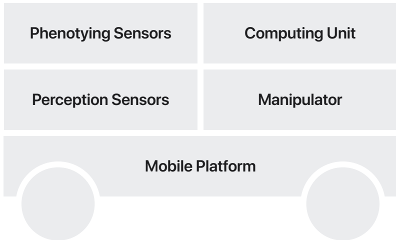


Figure 45: Key Components of Field Robots;
Created by the author based on (Xu & Li, 2022b)

The following chapters explore each of these components in differing degrees of detail.

In line with the research focus, there is special attention on phenotyping sensors and the exact parameters that the robot needs to measure. Additionally, emphasis is placed on the mobile platform, particularly regarding its technological specifications and setup.

Perception sensors, which are closely linked to the vehicle's navigation system, are addressed within the chapter on the mobile platform.

The digital backend, particularly the computing unit, receives only a brief mention since it is not the main focus of this thesis (see Chapter 1.5. Project Scope).

Manipulators, such as robotic arms, are not examined in detail, as field data collection generally occurs contactless, which eliminates the need for manipulators. In this concept, any manipulative actions are intended to be performed using the implements already available to the farmer (see Chapter 2.1.2.2. Mechanisation and Equipment).

2.3.1. Phenotyping Sensors - Sensor and Data Type Selection

2.3.1.1. Creating the Trait-Sensor-Relation Framework

Every digitisation process relies on data acquisition and interpretation. Data and data collection form the foundation of decision-support tools and data-driven management. In PA, data on individual fields and crops are gathered through observation, measurement, and sensing using various types of sensors mounted on mobile platforms such as drones, Unmanned Ground Vehicles (UGVs), or satellites (Karunathilake et al., 2023). This sensing process constitutes the fundamental core of PA (Hundal et al., 2023; Yuan et al., 2023). The collected data may pertain directly to plants, soil conditions, or the surrounding environment (Pieruschka & Schurr, 2024).

In agricultural research, various plant parameters are assessed with different sensor technologies. To determine the most relevant parameters and, thus, the appropriate sensors for this project, a comprehensive analysis is necessary. This chapter evaluates the effectiveness of several sensor technologies for field data collection in PA, investigating ideal sensor combinations that achieve a balance between information depth and cost-effectiveness in environmental monitoring. In addition to economic considerations, this study also outlines essential criteria for sensor selection.

Before selecting appropriate sensors for the project to integrate into the platform, it is essential to understand what needs to be measured and why. This chapter introduces the Trait-Sensor-Relation Framework, a decision-support tool designed to aid in sensor selection for farmer toolkits, ensuring efficient and meaningful data collection. The following chapters will provide a detailed, step-by-step explanation of the framework's development.

This chapter and the developed Trait-Sensor-Relation Framework address the subsequent research questions:

RQ 6. *Which sensor technologies are best suited for collecting field data in Precision Agriculture?*

RQ 6.1. *Which sensor combinations offer the best trade-off between information depth and cost-efficiency in environmental monitoring?*

RQ 6.2. *Beyond cost considerations, what are the most critical criteria for selecting sensors in Precision Agriculture and environmental monitoring?*

2.3.1.2. Field Phenotyping

Field phenotyping is the process of measuring and analysing plant traits in their natural environment using sensors, imaging technologies, and other tools to assess growth, health, and yield potential. This process involves capturing and evaluating complex plant characteristics, such as growth, development, geometric structure, and stress tolerance. The collective physical and physiological attributes of a plant are referred to as its phenotype (Thakur et al., 2023).

Moreover, the plant phenotype is significantly influenced by soil-related and environmental factors (e.g., weather conditions), which are also recorded during the phenotyping process (Pieruschka & Schurr, 2024). Monitoring the phenotype of crops requires non-invasive, high-throughput data collection across multiple scales (leaf, plant, field, or landscape level), time points (various growth stages), and data sources (different sensors and measurement tools) within the plant's natural environment (Yuan et al., 2023). This approach is essential for understanding plant responses to environmental stressors such as drought, salinity, and disease (Kolhar & Jagtap, 2023; L. Li et al., 2014; Narvaez et al., 2017; R. Qiu et al., 2018; Xu & Li, 2022b; Yuan et al., 2023; Zieschank & Junker, 2023).

Plant traits
Every plant has distinct traits, which are unique, measurable, quantitative parameters like height, leaf area, biomass, or chlorophyll content. These essential traits serve as the foundation for more intricate plant characteristics (L. Li et al., 2014). Traits can be broadly classified into morphological and physiological traits. Both categories are essential for understanding plant ecology, adaptation, and responses to environmental conditions (R. Qiu et al., 2018; Zieschank & Junker, 2023).

Morphological Traits
Morphological traits refer to the physical structure and form of a plant. These traits, such as plant height, are usually externally visible and can be measured directly.

Physiological Traits
Physiological traits, such as chlorophyll content, relate to the internal processes and functions of the plant. These traits are not always visible from the outside (R. Qiu et al., 2018; Zieschank & Junker, 2023).

Due to the complexity of plant phenotyping, a diverse range of morphological and physiological traits must be quantified to assess plant performance comprehensively (R. Qiu et al., 2018).

The list below summarises measurable plant traits from these two categories, identified in the literature, that are commonly used in automated plant phenotyping in PA (see Figure 46) (Crain et al., 2016; Das Choudhury et al., 2019; Gano et al., 2024; Kolhar & Jagtap, 2023; L. Li et al., 2014; Narvaez et al., 2017; Pérez-Ruiz et al., 2020; R. Qiu et al., 2018; Xie & Yang, 2020; Xu & Li, 2022b; Yuan et al., 2023; Zieschank & Junker, 2023).

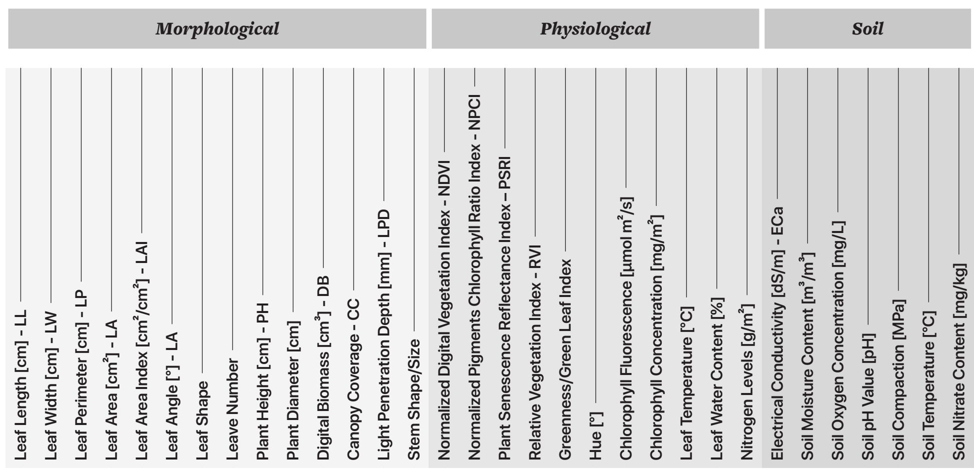


Figure 46: Commonly Measured Plant Traits and Soil Parameters

Relating Areas of Traits

Depending on their relevance, all phenotyping traits can be assigned to different plant characteristics. However, this categorisation is not mutually exclusive, as many plant traits contribute to multiple categories (Yuan et al., 2023)Some traits correlate strongly with only one specific category, such as yield, resistance, quality, or nutrition, while others provide valuable insights across multiple categories.

Yield
Yield is primarily determined by the plant's morphological characteristics. It essentially represents biomass production and is closely associated with the quantity of harvested organs.

Quality
Quality is influenced by differences in both morphological and physiological characteristics. Evaluating quality based only on morphological traits proves difficult. However, incorporating physiological traits, like nutrient content, results in more precise assessments.

Resistance
Resistance stems from a blend of multidimensional phenotypic data. It is shaped by numerous environmental elements, such as biotic stresses (including diseases, insect infestations, and weeds) and abiotic stresses (like drought, salinity, alkalinity, and flooding). These elements can greatly influence plant growth and survival.

Nutrition
Nutritional assessment is mainly based on physiological characteristics. These characteristics indicate aspects like soil nutrient availability, the nutrient requirements of plants, and the efficiency of nutrient uptake. Moreover, nutrient deficiencies show in morphological features, including the size and structure of the plants (Yuan et al., 2023).

Information Content of Different Traits

Most traits serve different functions and adapt to various environmental factors, interlinking in complex manners. These interconnections make it hard to analyse trait relationships and their specific roles through traditional correlation and cluster analysis techniques. An effective way to examine these multifaceted interactions is by utilising Plant Trait Networks (PTNs). PTNs offer a comprehensive framework for analysing and visualising the intricate relationships among various plant traits (N. He et al., 2020).

To illustrate which traits are most 'informative,' the relationships among them have been simplified. This strong simplification is necessary, as a complete PTN analysis would exceed the scope of this study. Additionally, the predictive power of traits may vary depending on the crop species. Based on previous studies (Botta et al., 2022; Cardone et al., 2020; N. He et al., 2020; Kolhar & Jagtap, 2023; Y. Li et al., 2016; Ouyang et al., 2021; R. Qiu et al., 2018; Rossato et al., 2017; Yuan et al., 2023; Zieschank & Junker, 2023) a simplified classification has been developed, indicating the extent to which specific traits allow for conclusions about the different categories. For instance, while traits such as plant diameter provide limited information, indices like the Normalised Difference Vegetation Index (NDVI) allow for more precise conclusions across multiple categories.

The graphic (see Figure 47) illustrates how various traits can be divided into morphological and physiological categories. Above each trait, it indicates the extent of information regarding yield, resistance, quality, or nutrients that can be obtained by evaluating that trait. In this framework, (1) signifies vague or indirect correlations, whereas (2) indicates direct correlations that enable more precise predictions.

For example, Chlorophyll content serves as a strong indicator of a plant's resilience (2) because it directly correlates with photosynthetic activity and overall plant health. Higher chlorophyll levels suggest robust photosynthesis, which leads to superior growth and increased yield (1). While chlorophyll content offers a rough estimate of yield, a more accurate prediction can be achieved by assessing biomass, as it reflects the actual harvested volume.

Conversely, biomass can also signify resilience (1), since only plants that efficiently perform photosynthesis and possess high chlorophyll levels can accumulate substantial biomass (Cheng et al., 2025; Jiang et al., 2018; Mohan et al., 2022; Mu et al., 2024; Rowland et al., 2020; SAMUOLIENĖ et al., 2019; Wang et al., 2022). Therefore, while certain traits allow for accurate predictions, others provide indirect insights into specific aspects, and some can only be effectively understood when combined with supplementary data (Expert Interviews, 2025).

It is important to acknowledge that this is a greatly simplified representation. The table is intended solely as a guide for selecting sensors. The information conveyed by specific traits can vary significantly among different crop species.

Morphological

Trait	Yield	Resistance	Quality	Nutrient
Leaf Length [cm] - LL	2	1	1	0
Leaf Width [cm] - LW	2	1	1	0
Leaf Perimeter [cm] - LP	1	1	1	0
Leaf Area [cm^2] - LA	2	1	1	1
Leaf Area Index [cm^2/cm^2] - LAI	2	1	1	1
Leaf Angle [°] - LA	1	2	0	0
Leaf Shape	0	0	2	0
Leave Number	1	1	1	0
Plant Height [cm] - PH	2	1	1	1
Plant Diameter [cm]	1	0	0	0
Digital Biomass [cm^3] - DB	2	2	1	1
Canopy Coverage - CC	2	1	1	1
Light Penetration Depth [mm] - LPD	1	1	1	0
Stem Shape/Size	1	2	0	0

Physiological

Trait	Yield	Resistance	Quality	Nutrient
Normalized Digital Vegetation Index - NDVI	2	1	1	2
Normalized Pigments Chlorophyll Ratio Index - NPCI	1	2	1	1
Plant Senescence Reflectance Index - PSRI	1	2	1	0
Relative Vegetation Index - RVI	2	0	1	2
Greenness/Green Leaf Index	0	1	2	1
Hue [°]	0	1	2	1
Chlorophyll Fluorescence [µmol m^2/s]	1	2	1	1
Chlorophyll Concentration [mg/m^2]	1	1	1	2
Leaf Temperature [°C]	1	2	0	1
Leaf Water Content [%]	1	2	1	1
Nitrogen Levels [g/m^2]	2	0	1	2

Soil

Trait	Yield	Resistance	Quality	Nutrient
Electrical Conductivity [dS/m] - ECa	0	2	0	1
Soil Moisture Content [m^3/m^3]	1	1	1	1
Soil Oxygen Concentration [mg/L]	1	1	1	1
Soil pH Value [pH]	1	1	1	2
Soil Compaction [MPa]	1	1	1	1
Soil Temperature [°C]	1	0	1	1
Soil Nitrate Content [mg/kg]	2	0	2	2

Figure 47: Information Value of Various Plant Traits

However, with the continuous advancements in AI systems, particularly convolutional neural networks (CNNs), the informational value of plant traits can be increasingly refined and better interpreted. By integrating multiple traits, AI models can provide a holistic perspective, enhancing the understanding of how various factors influence plant growth and development. Therefore, it can be assumed that even a combination of multiple 'weak' (low-information) traits can yield significant insights when analysed using AI-driven approaches (Hati & Singh, 2021). It can significantly enhance the informational content derived from standard morphological and physiological plant traits. The integration of AI and machine learning (ML) techniques enables more comprehensive data analysis and interpretation, leading to deeper insights into plant biology (Cembrowska-Lech et al., 2023).

2.3.1.3.Sensors

The selection of sensor technology is inherently linked to the choice of plant traits to be measured. Traits and sensors are interdependent. While some sensors are designed for highly specific measurements, others can be used to capture multiple traits. Not every trait, however, needs to be measured directly to yield meaningful plant data. Strong correlations between certain traits allow for indirect assessments, where measuring one trait can provide reliable insights into another (R. Qiu et al., 2018).

A single trait can be evaluated using various sensor technologies. For example, plant height can be measured with an RGB camera that employs AI analysis or with a LiDAR system. The choice of sensor influences both the measurement accuracy and the range of traits that can potentially be assessed. Depending on the technology, sensors may capture one trait or several, aiding in evaluating plant characteristics. Therefore, choosing the appropriate sensor should match the intended application, ensuring adequate and pertinent measurements.

Using plant height as an example, both LiDAR technology and RGB cameras equipped with AI analysis can measure this metric, but they vary significantly in their capabilities and limitations. LiDAR provides highly accurate depth readings and functions efficiently under various lighting environments, ensuring precision; nonetheless, it comes with high costs and demanding computational needs. In contrast, RGB cameras with AI are more cost-effective and readily available but depend on substantial training data and are affected by lighting variations. The balance between resolution, cost, and processing demands significantly influences the practicality and success of sensor deployment.

The schematic overview illustrates the complexity of sensor selection (see Figure 48). The choice of sensors directly determines which traits can be measured and in what quality and quantity, influencing the depth of information that can be extracted. At the same time, every trait has a different information value, allowing for agricultural decision-making.

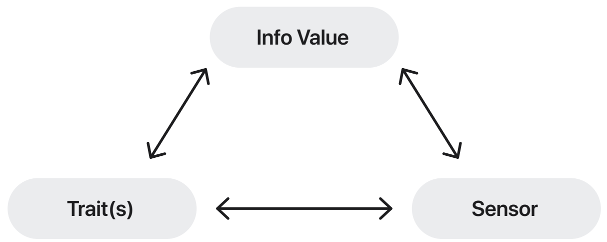


Figure 48: Relation between Trait, Info Value and Sensor

Moreover, several critical factors must be thoughtfully evaluated to achieve the ideal balance among accuracy, cost, and practical utility in precision agriculture. It's not solely about how closely a sensor aligns with specific traits—technical specifications and limitations are equally significant. These factors encompass the clarity of the sensor's images (in terms of spatial and spectral resolution), the overall cost, and its computational demands(Xie & Yang, 2020). Additionally, it is vital to consider the sensor's operational range, durability, and ability to withstand challenging environments.

Relevant plant phenotyping and trait estimation sensors have been identified and added to the table. In addition to listing the types of sensors currently available and in use, they have also been mapped to the specific plant traits they can measure or have been used to estimate. A mark in the matrix shows which traits the correlating sensor can measure (see Figure 49) (Crain et al., 2016; Deery et al., 2014; Fountas et al., 2020; Gano et al., 2024; Guri et al., 2024; Karunathilake et al., 2023; L. Li et al., 2014; Narvaez et al., 2017; Neupane & Baysal-Gurel, 2021; Oliveira et al., 2021; R. Qiu et al., 2018; Stafford, 2013; Villa-Henriksen et al., 2020; Xie & Yang, 2020; Xu & Li, 2022b; H. Zhang et al., 2023). However, it is essential to note that this mapping may evolve with ongoing advances in artificial intelligence. For example, while it was previously impossible to estimate plant volume using a standard RGB camera, recent technological progress has enabled algorithms to extract such information from RGB data alone (Raja et al., 2021).

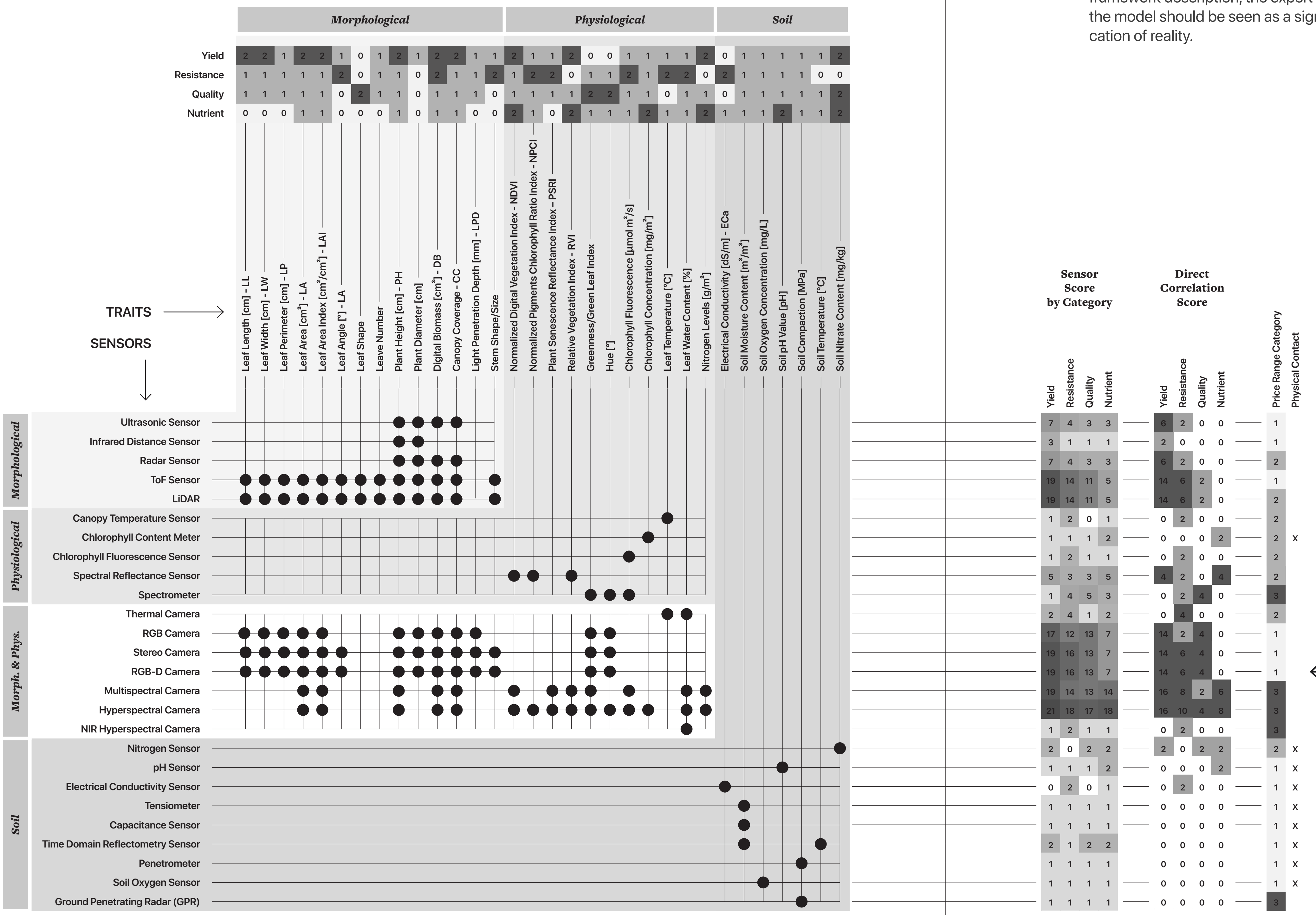
2.3.1.4.Using the Trait-Sensor-Relation Framework

To determine the best sensors for this project, a score was computed for each sensor across four criteria: yield (Y), resistance (R), quality (Q), and nutrient content (N). This score reflects the overall value of all traits that a sensor can potentially measure within each criterion. For instance, if a sensor measures trait A with a yield value of 2 and trait B with a yield value of 1, it achieves a total yield score of 3.

The scores appear on the right as a heatmap (see Figure 49), reflecting the theoretical information potential of each sensor, under the assumption that it measures all traits it is technically capable of detecting. However, it's important to note that measuring two weakly correlated traits (1) related to a given category is not the same as measuring a single trait with a strong correlation (2). To address this distinction, a second heatmap is presented on next to it, illustrating the direct correlation score, which only considers those traits with strong correlations (2) to the relevant category.

Two additional factors were considered for the final selection of sensors: price category and the requirement for physical contact. The price category is a straightforward classification: category A represents average prices in the two-digit range, category B encompasses three-digit prices. In contrast, category C includes sensors priced at four digits or more. Since cost presents a considerable barrier to farmers adopting precision agriculture technologies, all category C sensors were eliminated from consideration. Sensors requiring physical contact with the test object (plant or soil) were designated with an 'X'. These also were excluded, as they would greatly complicate their integration into an autonomous platform.

It must be mentioned that the computational requirements of each sensor are also essential for the selection process. A deeper integration of these requirements, particularly for each sensor, along with an appropriate ranking, would be advantageous. However, this analysis goes beyond the scope of this thesis. Nonetheless, this aspect should be considered more in future decision-making processes.



RGB-D camera is the most promising choice due to its strong performance in both information scoring and affordability.

Figure 49: Final Trait-Sensor-Relation Framework

In summary, the framework indicates that both the stereo camera and the RGB-D camera are the most promising choices due to their strong performance in both information scoring and affordability.

To validate the relevance of the framework, the topic of clustering and its correlation with specific categories identified in the literature was also discussed during an expert interview with an independent research scientist holding a Doctorate in Natural Sciences. As previously mentioned in the framework description, the expert confirmed that the model should be seen as a significant simplification of reality.

The expert underscored that the significance of a measurement largely relies on its application—whether it acts as a criterion for a specific intervention (cause-effect) or as an indicator of the system's overall state. Additionally, it was noted that certain values gain meaning only when interpreted alongside others. For instance, measuring leaf length in isolation offers very little insight; its relevance emerges when assessed with other attributes such as leaf width or shape. While some parameters may be more meaningful when considered alone, others only elucidate their significance in combination.

“They belong together. From the shape of the leaf, the way it grows, and the flatness—how flat the blade is and how the plant holds the leaf—you can read an incredible amount. If you know how to interpret that, you can understand a lot about the plant’s condition. A lot! But if you isolate just one of these values? No.”

– Expert Natural Sciences

The expert also noted that the fewer data points you collect, the more difficult it becomes to interpret them correctly. This is well summarised in the following quote:

“In my experience, the fewer data you collect, the better you need to be at interpreting them.”

– Expert Natural Sciences

Thus, measuring various traits is crucial for obtaining reliable results. Gathering diverse data, not just focused on plants or soil, but also including other factors like environmental factors, facilitates more precise conclusions, while limited data can hinder interpretation. The RGB-D camera, known for its capability to capture a range of traits, is selected for data collection in this thesis, as it aligns well with the framework. Its potential for enhancing data interpretation through AI further confirms the RGB-D camera as a cost-effective and appropriate choice, given its proficiency in capturing both colour and depth information.

2.3.1.5. The Role of Bioindicators in Informed Decision-Making

Phenotyping, outlined in the previous chapter, entails a multifaceted process. Ecosystem health evaluations should not rely only on isolated indicators. Adopting a holistic perspective is essential, as single measurements rarely capture the complexities of natural systems. Specific parameters possess greater informational value than others, indicating that this inherent hierarchy could improve data collection strategies.

This inspired the concept of utilising nature as a dependable indicator. The idea involves starting with the insights that ecosystems provide through particular species. Instead of prioritising specific soil or plant measurements, this strategy emphasises how insects and animals, particularly those sensitive to environmental shifts, can act as proxies for evaluating ecosystem health and informing farming choices.

This can be illustrated through a simple analogy: when evaluating a car's functionality, one typically doesn't examine every engine component separately. Instead, the standard approach is to start the engine. If it operates correctly, it's assumed that the essential subsystems—like the battery, ignition, and fuel delivery—are working adequately. A more detailed assessment of individual parts is only conducted if the engine fails to start. This approach saves time and resources while still offering a reliable diagnosis. In ecosystem monitoring, specific species can act as bioindicators—organisms whose presence indicates that key environmental conditions are within appropriate ranges. From this hypothesis, two key research questions were derived that will be assessed in this chapter:

RQ 4.1. *What role do bioindicators and indicator species play in monitoring environmental changes and assessing ecosystem integrity?*

RQ 4.2. *How do temporal delays and local biases affect the reliability of bioindicators in ecosystem evaluation?*

To investigate this, an interview was conducted with a biologist. The expert endorsed this hierarchical measurement strategy, highlighting its effectiveness and strategic importance. Rather than gathering thousands of data points at the outset, it is more efficient to start at the top of the data hierarchy and only dig deeper when anomalies arise. For instance, the presence of earthworms suggests that factors such as soil moisture, aeration, pH, and organic matter levels are likely within acceptable limits. Instead of measuring each factor individually, monitoring earthworms provides a holistic and efficient evaluation of soil health. If these creatures are absent, more detailed measurements can follow (Expert Interview, 2025).

"The higher you go in the system—say, if earthworms are present—then you already know that many other factors must be in place. Otherwise, they wouldn't be there at all."

– Expert Natural Sciences

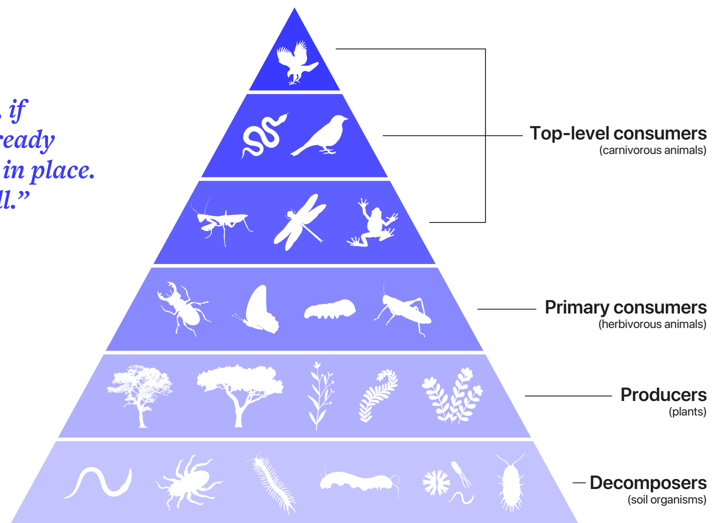


Figure 50: Ecological pyramid; Created by the author based on (Ueda, n.d.)

Tools like Soildiag, created by botanist Gérard Ducerf, embody this concept. The app evaluates images of indicator plants to estimate essential soil properties such as pH, biological activity, and organic matter, without requiring direct sampling (Soildiag, n.d.). Besides plant indicators, particular animal species could also serve as valuable reference points. The presence of predatory insects like hoverflies or ladybugs indicates a healthy ecosystem, while their absence signals degradation. For example, hoverflies that prey on aphids demonstrate natural pest control, whereas the presence of dung beetles in meadows signifies a functioning nutrient cycle.

"We should be paying closer attention to insect species in the field. They offer highly specific and meaningful ecological insights—we simply choose not to see them."

– Expert Natural Sciences

Multisensory Approaches: The Role of Acoustic Signals

Acoustic signals were also highlighted as an underutilised yet valuable source of ecological data. Field biologists do not rely solely on visual cues—they also listen. The calls of specific birds or the chirping of crickets can reveal much about local ecosystems. Advances in AI now make it increasingly feasible to automate the identification of these auditory signals. By integrating sound analysis into monitoring systems, beyond the dominant use of cameras, ecological assessments could become even more comprehensive.

"If I walk a transect and hear selected bird species, I know they're there. Recognising bird calls or cricket chirps can provide valuable data. Sound is a vital layer of information, but we often ignore it in favour of visual data."

– Expert Natural Sciences

Addressing Spatial and Temporal Biases

Methodological strategies can alleviate concerns regarding spatial and temporal biases in bioindicator data. Spatial bias is frequently countered by employing transects—systematic sampling lines from which data is gathered at regular intervals, typically every 5 or 10 meters. This method effectively uncovers ecological gradients and spatial patterns. Temporal delays between environmental changes and ecological responses are generally minimal. Although some species may respond slowly, others can react almost instantaneously to environmental shifts (Wu et al., 2020).

Limitations in Degraded Ecosystems

Although this approach shows potential, it has limitations. A significant challenge occurs in already degraded ecosystems. In numerous regions, indicator species have disappeared due to severe environmental degradation. Consequently, there are no organisms left to act as ecological reference points.

"We've lost 90 per cent of insect biomass. Predators have vanished from conventional farmland—they're just no longer there. That means we've ended up in a degraded system where pests remain, but the natural predators are missing. So, you'll have to accept that, and measure at that lower level [individual plant parameters]."

– Expert Natural Sciences

Conventional measurements, like plant-based sensor data, are essential in these environments. Bioindicators can only operate in healthy ecosystems that can sustain them.

Implications for Sensor Selection and Monitoring Strategy

In conclusion, bioindicators can serve as valuable reference points for ecosystem monitoring. However, relying solely on biological indicators is often not feasible in heavily degraded systems. Therefore, the proposed monitoring strategy should begin with plant-based sensor measurements.

As ecosystems recover and indicator species re-emerge, the strategy can gradually shift to incorporate bioindicator-based evaluations, using these organisms as key proxies for assessing ecosystem health. Similar to how canaries historically provided early warnings in coal mines, indicator species can indicate both recovery and potential underlying ecological issues. Consequently, a hierarchical, species-informed approach can enhance environmental monitoring, making it more efficient and better aligned with the principles of nature.

2.3.1.6.Conclusion Recording Technologies

This chapter guides on choosing sensor technologies to advance the design concept. The Trait- Sensor- Relation Framework identifies several key factors to aid in sensor selection. Although intended as an initial guide for this thesis, it can also serve as a starting point for broader discussions about the complex task of selecting suitable technologies. As noted, sensor selection is not universally applicable; it demands careful consideration of cost, accuracy, scalability, and environmental suitability.

The proposed scoring and evaluation strategy underscores the advantages of affordable, non-contact sensors such as RGB-D cameras, particularly due to their versatility. As artificial intelligence advances, the value of the simple data these sensors generate is expected to increase significantly. Enhanced data interpretation capabilities will likely yield deeper insights, allowing the same hardware to improve functionality through straightforward digital backend updates, making these sensors a future-proof solution.

A comprehensive review of artificial vision systems used for agricultural characterisation and detection has been provided by (Narvaez et al., 2017). This work intentionally does not include a detailed technical description of individual sensor technologies, as this information is already thoroughly covered in numerous scientific studies, including those by (Crain et al., 2016; Deery et al., 2014; Fountas et al., 2020; Gano et al., 2024; Guri et al., 2024; Karunathilake et al., 2023; L. Li et al., 2014; Narvaez et al., 2017; Neupane & Baysal-Gurel, 2021; Oliveira et al., 2021; R. Qiu et al., 2018; Stafford, 2013; Villa-Henriksen et al., 2020; Xie & Yang, 2020; Xu & Li, 2022b; H. Zhang et al., 2023).

The chapter also emphasises the role of bioindicators in environmental monitoring. While the expert interview supported the core hypothesis of their usefulness, they also highlighted certain limitations. Bioindicators such as earthworms and pollinators can provide quick, comprehensive insights into ecosystem health; however, their effectiveness diminishes in highly degraded environments.

To tackle this issue, a hierarchical monitoring strategy is recommended: beginning with robust plant-based data collection and progressively integrating bioindicators as ecosystem conditions improve. The significance of audio data in monitoring has also been acknowledged and will be further included in the design concept.

Ultimately, this integrated approach, melding sensor technologies (both visual and auditory) with various data sources (including plant parameters and bioindicators), provides a flexible, scalable framework for future agricultural monitoring platforms.
It is essential to mention that several soil-related parameters were excluded from the selection process due to their need for physical contact. While this exclusion is justifiable in an automated system, these parameters still hold value for manual assessments by farmers and should receive greater focus in future studies.

2.3.2.Mobile Platform

The carrier platform—whether a four-wheel tractor, single-axle machine, or another towing device—serves as the foundation of agricultural mechanisation (see Chapter 2.1.2.2. Mechanisation and Equipment) (Expert Interviews, 2025). This chapter outlines the differences between various platform types, whether ground-based or aerial, and provides an overview of their drive mechanisms and guidance systems (for autonomous platforms). The aim is to support informed decision-making regarding the most suitable mobility concept for small farms.

2.3.2.1.Ground vs. Aerial Platforms

Agricultural autonomous platforms can be broadly divided into aerial and ground systems (Xu & Li, 2022a), each presenting unique benefits and drawbacks. Regarding data collection, UAVs provide distinct advantages: they are more efficient and capable of covering wider areas (Xu & Li, 2022a). Their ability to fly avoids interference from ground-level obstacles like rocks, holes, terrain variations, and branches (Oliveira et al., 2021). On the other hand, the repeated movement of UGVs on the ground leads to increased soil compaction, which poses a significant problem in agriculture.

UAVs encounter several limitations. Their payload capacity is notably constrained, restricting the types of sensors and equipment they can transport. Furthermore, UAVs are more vulnerable to weather conditions like wind and rain (Xu & Li, 2022a; Oliveira, Moreira, & Silva, 2021). While flying offers advantages, it typically results in reduced ground-level detail and limits close-range sensing because of the greater distance between plants and the sensor (Munasinghe, Perera, and Deo, 2024). UGVs theoretically have the advantage of controlling lighting in enclosed spaces if needed (Ren et al., 2024) and providing a more adaptable viewing angle, unlike UAVs, which are confined to top-down perspectives of the canopy (Xu & Li, 2022a).

Additionally, trees in the field, which are essential for biodiversity, present greater challenges for airborne sensing technologies. This is not only because of the risk of collisions with branches (similar to power lines) (Oliveira et al., 2021), but also due to their ability to block visibility beneath the canopy (Ren et al., 2024). Drone flight time further limits UAV capabilities. Unlike UGVs, UAVs cannot easily support large, heavy batteries, which greatly limits their operational time (Oliveira et al., 2021; Ren et al., 2024). In contrast, UGVs encounter fewer regulatory and legal limitations, as they remain on the ground (Ren et al., 2024). Figure 51 illustrates the pros and cons of each system.

UGVs	UAVs	
+	–	Flexibility (Additional Tasks)
–	+	Area Coverage
–	–	Obstacle avoidance
–	+	Soil Impact
+	–	Payload Capacity
+	–	Weather Resistance
+	–	Detail Resolution
+	–	Viewing Angle
+	–	Operational Time
+	–	Regulatory Limits

Figure 51: Comparison of UGVs and UAVs

Recently, hybrid platforms have attracted attention, including UAVs that land on UGVs for recharging and ground robots equipped with tethered aerial components and „perch-and-stare" capabilities (Munasinghe et al., 2024). While this combination leverages the strengths of both systems, it also brings out their weaknesses. Combining both UAVs and UGVs raises expenses, demands more infrastructure, and adds to the system's overall complexity (Pretto et al., 2021).

One key distinction between UGVs and UAVs is that UGVs offer more functionality beyond data collection—they can also execute a range of farming tasks. For instance, they can be fitted with tools or manipulators to perform activities like ploughing, which UAVs are unable to do (Pretto et al., 2021).

As previously noted (see Chapter 2.2.3.2. Technological Factors), data collection alone often does not provide sufficient immediate value to justify the use of robotic systems on small-scale farms. Therefore, this thesis focuses on ground-based robots, which can support both monitoring and practical field tasks. Flexibility is a key factor in precision agriculture for small farms, and ground-based solutions, compared to airborne solutions, are more suited to meet this need. The following chapter will delve deeper into the various drive mechanisms that can be employed for ground-based robotic systems.

2.3.2.2. Drive Mechanisms

Phenotyping robots are typically categorised into three types according to their drive mechanisms: wheeled, tracked, and wheel-legged. Wheeled-robots can be further divided into those with limited mobility and those with full mobility (see Figure 52) (Xu & Li, 2022b).

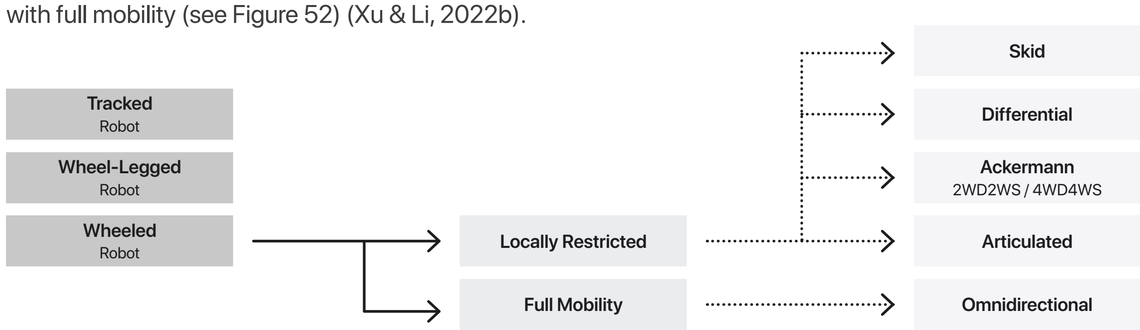


Figure 52: Drive Mechanisms; Created by the author based on (Xu & Li, 2022b)

This section provides a brief overview of each mechanism. A custom illustration on the right (see Figure 53) visually depicts the structure of each system. Actively driven wheels are labelled (A), while passive wheels are denoted (P).

Tracked
Tracked robots utilise continuous tracks instead of wheels, enhancing ground contact and adapting well to difficult terrains like muddy and uneven fields. They function with lower ground pressure, which makes them perfect for soft surfaces. Their movement systems are like those found in differential drive wheeled robots (Bruzzone et al., 2022).

Wheel-Legged
Wheel-legged robots merge the benefits of wheels with articulated legs, delivering both speed and enhanced adaptability to various terrains. They offer manoeuvrability similar to that of four-wheel drive and four-wheel steering (4WD4WS) systems. However, their increased mechanical complexity and expense render them less durable and economically viable for most phenotyping applications, where these advanced features may be excessive (Zhu et al., 2024).

Wheeled
Locally constrained wheeled robots—particularly those with skid-steer and differential drive systems—are appreciated for their simplicity and affordability. These systems closely resemble tracked locomotion, particularly in their capability to rotate on the spot by adjusting the speed and direction of the wheels. Skid-steer robots commonly feature four powered wheels and manoeuvre by varying the speeds of these wheels. On the other hand, differential drive robots operate with two powered wheels and typically include one or more passive caster wheels to maintain balance and enhance manoeuvrability. While both types can perform zero-radius turns, skid-steer robots depend on lateral wheel slippage for turning, leading to decreased power efficiency, increased tire wear, and possible soil disturbance. Although differential drive robots can also experience slippage, it is significantly less frequent, leading to lower energy lossand reduced impact on soil compared to skid-steer robots. Nonetheless, differential drive systems can face steering inaccuracies due to unequal traction or rolling resistance among the wheels, potentially leading to unintended deviations in direction (Xu & Li, 2022b).

Ackermann steering, commonly used in cars, provides a familiar and efficient means of navigation. In this system, either two or all four wheels can be powered, allowing for stable and controlled motion on solid ground. However, its primary limitation is the large turning radius, which becomes a disadvantage in constrained environments, such as at the edges of crop fields, where space is limited (Q. Qiu et al., 2018).

Articulated steering offers a compelling alternative, particularly in off-road scenarios. In this design, the robot is split into front and rear segments connected by a vertical hinge, with steering achieved by changing the angle between the two halves. While this setup enhances manoeuvrability and reduces the required turning space, it comes at the cost of increased mechanical complexity compared to Ackermann steering (Delrobaei & McIsaac, 2011).

Fully mobility wheeled robots provide enhanced steering capabilities. Certain models employ a two-wheel drive and two-wheel steering arrangement (2WD2WS), while others use a four-wheel drive and four-wheel steering configuration (4WD4WS), which offers more precise control. This configuration boosts off-road performance but introduces mechanical complexity. Omnidirectional robots take mobility a step further, allowing movement in any direction without needing to rotate the chassis. Although this feature enables better adaptability to different terrains, it also elevates both system costs and control complexities (Tagliavini et al., 2022).

To find the optimal solution for the drive mechanism of the ground-based system, multiple decision factors identified in the research have been chosen and prioritised using a Harris profile (see Figure 53).

Manual Operation	- Must be operable manually (e.g. pushed via handle) to reduce reliance on automation.
Mechanical Complexity	- Favour a straightforward design for durability and easy maintenance.
Cost	- Minimise production and upkeep costs (e.g., fewer motors).
Steering Precision	- Ensure accurate autonomous navigation for reliable phenotyping.
Manoeuvring Space	- Support a small turning radius for confined farm spaces.
Terrain Adaptability	- Operate reliably on rough, soft, or uneven ground.

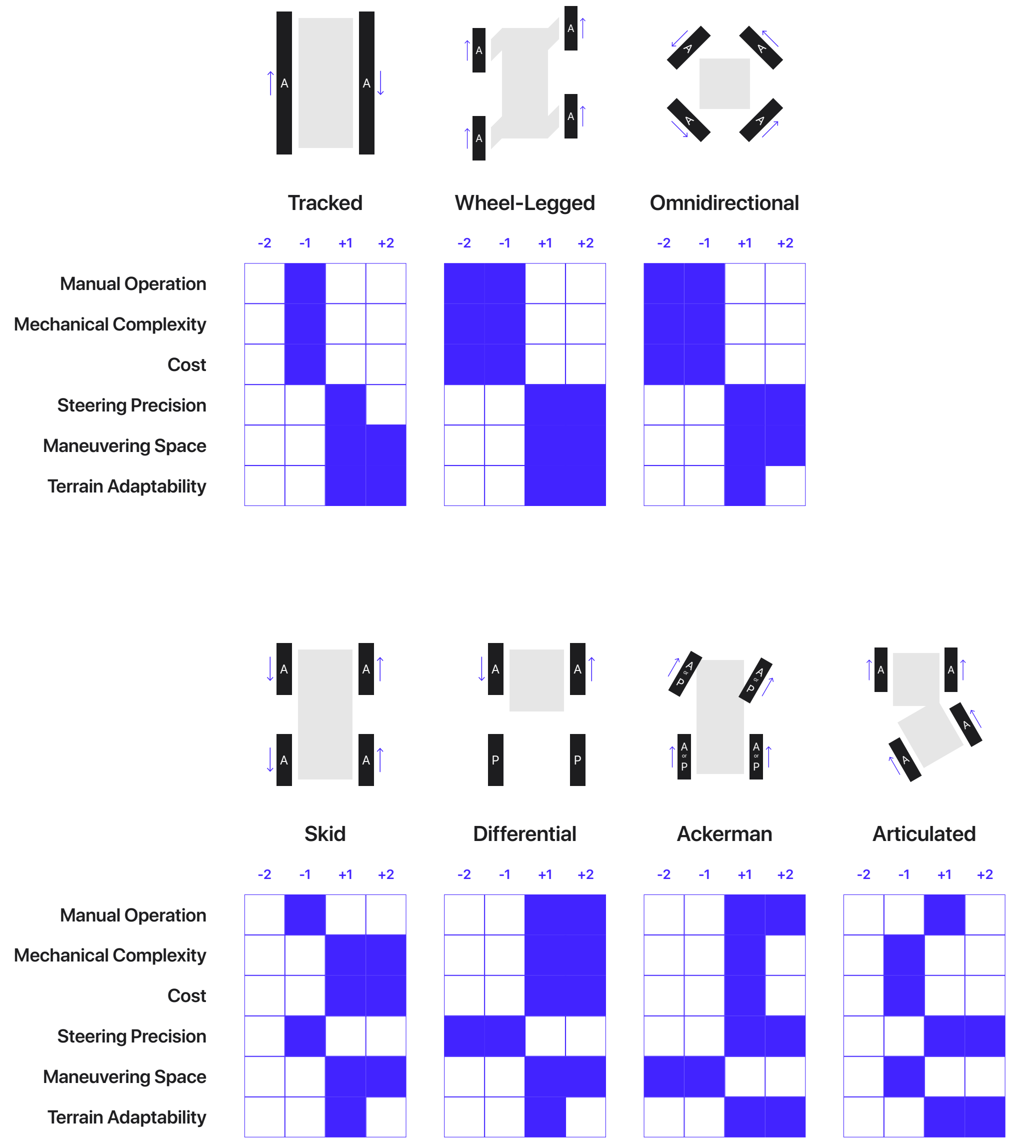


Figure 53: Evaluation of Drive Mechanisms Using Harris Profiles

The Harris profiles indicate that differential steering is the most effective configuration, primarily due to its affordability and mechanical simplicity. These features render it ideal for creating dependable and easily built robots. A key drawback of differential steering is its lower steering precision, primarily due to the uncontrolled swivel of passive caster wheels. Nevertheless, this limitation can be significantly alleviated by fine-tuning the pivot offset of the caster wheels, which improves straight-line tracking.

2.3.2.3. Perception Sensors – Navigation

Navigation plays a vital role in robotic automation, presenting three main challenges: localization, path planning, and map building. A variety of sensor technologies are commonly utilised to tackle these issues. GNSS and IMU deliver global positioning and orientation, whereas vision and LiDAR sensors facilitate accurate localization and obstacle detection. These sensors frequently collaborate within Simultaneous Localisation and Mapping (SLAM) frameworks to promote real-time awareness of the environment and assist with navigation (Xu & Li, 2022b).

GNSS-Based Navigation
GNSS is extensively utilised for robot localisation, particularly within agricultural settings. High-precision systems such as RTK-GNSS provide centimetre-level accuracy and are frequently employed in path-following operations for autonomous machinery (Oliveira et al., 2021). Nevertheless, GNSS performance can diminish due to signal obstructions from tree canopies, multipath interference, radio frequency disturbances, and insufficient heading data. To address these challenges, GNSS is often integrated with additional sensors like IMUs and wheel encoders. In situations where GNSS reliability is uncertain, or in rapidly changing environments, vision-based and LiDAR-based methods are favoured for their ability to deliver real-time obstacle detection and mapping (S. Li et al., 2023). Although the high subscription costs of RTK correction signals have posed a barrier to widespread adoption (Lowenberg-DeBoer et al., 2020), there are growing efforts within the EU to provide these services free of charge to farmers. For instance, Austria has been offering free RTK correction signals for agricultural use since February 2021 (Hirt, 2024).

Vision-Based Navigation
Vision-based navigation allows robots to track crop rows through machine vision techniques. Typically, RGB cameras are employed to identify these rows and evaluate the robot's orientation concerning them. Integrating stereo vision systems enhances depth perception, boosting performance under varying lighting conditions and amidst weeds. However, this approach can be sensitive to changes in lighting and low-texture environments. To enhance robustness, vision systems are often paired with GNSS: vision guarantees accurate row-following, while GNSS aids navigation between rows or in visually compromised situations (S. Li et al., 2023; Xu & Li, 2022b).

LiDAR-Based Navigation
LiDAR operates by sending rapid pulses of laser light and measuring the time it takes for these pulses to bounce back from nearby objects. By determining distances using the speed of light, it creates a precise 3D representation of the surroundings. Although highly accurate, LiDAR can generate rough or noisy data and sometimes misidentify vegetation, like grass or leaves, as obstacles. Integrating LiDAR with vision sensors improves object classification and eliminates irrelevant data points, thus enhancing structural detection and obstacle avoidance (Stronzek-Pfeifer et al., 2023).

Small-scale farms need a navigation system that is accurate, affordable, and durable - traits often missing from single-sensor solutions in actual agricultural scenarios. A tiered sensor fusion strategy provides a more dependable alternative. Combining an RTK-GNSS receiver with an IMU and wheel encoder achieves centimetre-level positioning while retaining heading during GNSS outages. Stereo RGB cameras aligned with crop rows facilitate accurate local lane navigation, even amidst weeds. An optional 2D LiDAR layer can improve safety by identifying obstacles that the camera system might miss. Additionally, it is helpful to consider the dual use of sensors already in place for phenotyping (see Chapter 2.3.1.6. Conclusion Recording Technologies). If an RGB-D camera is already being used for phenotyping, it can also support navigation, necessitating only the addition of the RTK-GNSS, IMU, and wheel encoder. This multi-purpose approach minimises hardware redundancy and enhances cost-efficiency.

2.3.2.4. Computing Unit

In a phenotyping robot, the computing unit performs two primary functions: autonomous navigation and data collection, which can operate independently. While compact and energy-efficient single-board and embedded systems can be utilised, their processing power is often limited. As a result, it's common to employ separate computing units for navigation and data collection. This approach facilitates task-specific optimisation, for instance, leveraging a high-performance PC to manage large sensor data, and enhances modularity for smoother sensor integration and upgrades. However, this also introduces communication complexity and increases hardware costs (Xu & Li, 2022b).

Since this project aims to create a highly flexible system, separate computing units will be implemented to allow for quick and simple sensor swapping, with one computing unit designated explicitly for autonomous navigation.

Software and Artificial Intelligence (AI) play a crucial role within the realm of computing power. This thesis will not explore these topics further because they are considered established technologies in precision agriculture and fall outside the main focus of this work.

Chapter 3

Design Development

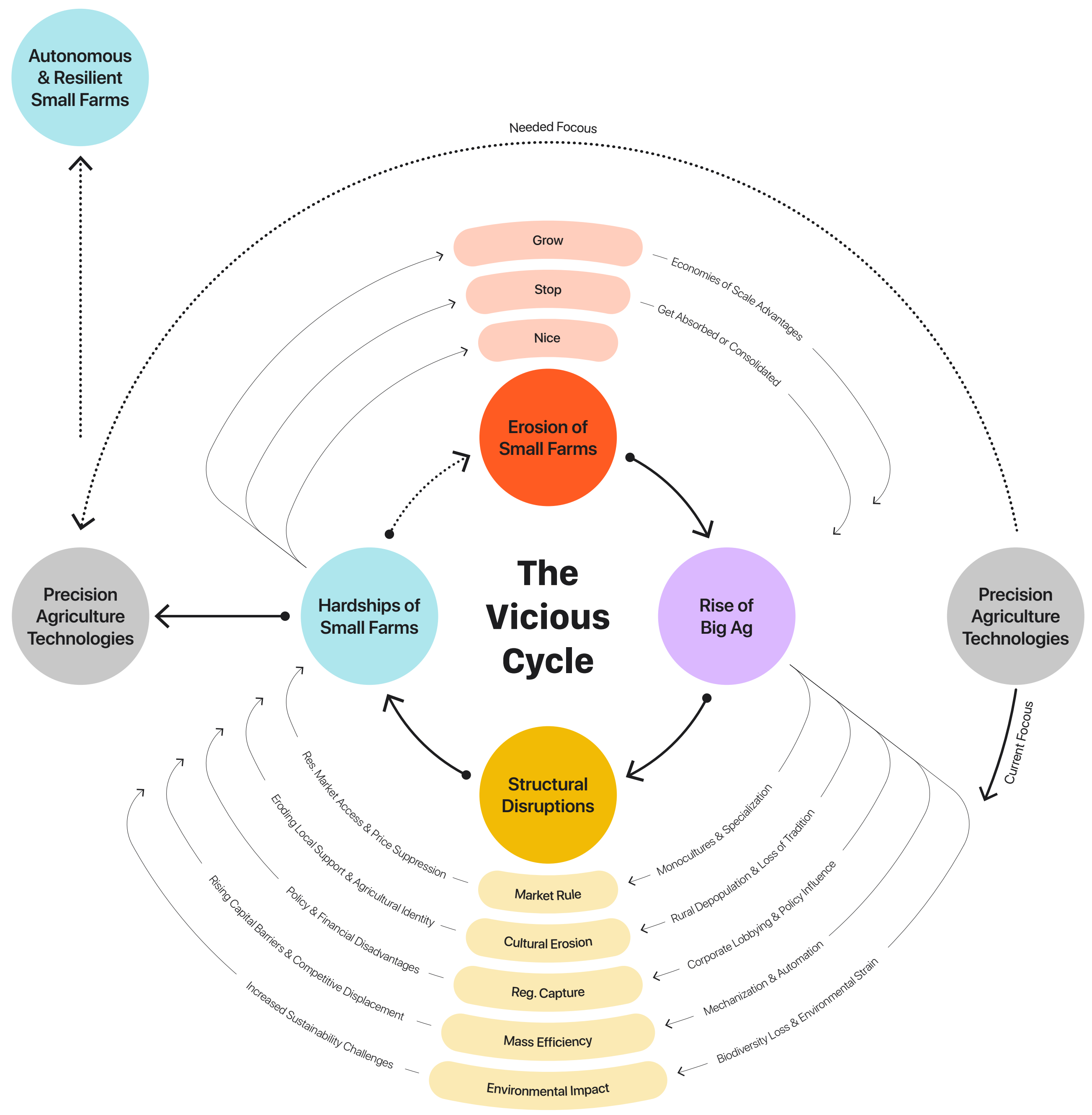


Figure 54: Breaking the Vicious Cycle: Repositioning Precision Farming Technologies

3.1. Synthesis of Insights

3.1.1. Summary of Theoretical and Empirical Findings

The survival of small farms is not merely important - it is crucial to the future of our food system. Yet the trajectory of the past several decades paints a stark picture. Small-scale farming is being systematically undermined. Despite policy efforts like the European Union's Common Agricultural Policy offering financial lifelines, subsidies alone cannot counteract the structural forces driving small farms toward extinction. These farms are essential pillars of rural economies and irreplaceable guardians of agricultural biodiversity. But the odds are stacked against them. Faced with mounting challenges, they are being pushed out, making way for the relentless expansion of industrial agriculture.

As small farms disappear, industrial agribusinesses tighten their grip. With access to vast capital, infrastructure, and economies of scale, Big Ag has engineered a playing field in which smallholders are set up to fail. The more dominance these corporations gain, the more entrenched the system becomes. This is not simply market evolution—it is structural displacement. It leads to the erosion of community-based food systems and ecological resilience. And along with the disappearance of small farms, sustainable agriculture is buried as well.

The created Figure 54 illustrates this dynamic through the concept of a "vicious cycle." The erosion of small farms fuels the rise of Big Ag, which in turn drives more profound structural disruptions - monocultures, regulatory capture, environmental degradation, and the displacement of rural identities. These disruptions, in turn, worsen the conditions for smallholders, intensifying their hardships and pushing them further toward exit or absorption. As small farms vanish, the agricultural landscape becomes increasingly homogenised, less diverse, and more vulnerable.

A key insight from this graph is that Precision Agriculture Technologies (PATs), while often promoted as solutions, are currently being deployed at the wrong leverage point in this cycle. Instead of disrupting the cycle, they are reinforcing it - optimising efficiency for large-scale operators while neglecting the needs and realities of small farms. While promises abound that PATs will make Big Ag more sustainable, this approach is fundamentally flawed. Making industrial farming slightly more efficient does not solve its core problems - it merely postpones collapse.

What agriculture needs is not marginal improvement through technology, but radical transformation. We need a diverse network of small farms - autonomous, resilient, and locally rooted - cultivating a wide range of crops and strengthening local economies. These farms must serve as both stewards and beneficiaries of their ecosystems. To achieve this, we must redirect innovation. Precision agriculture must be decoupled from its current trajectory and repositioned as a tool to empower small farms.

This means developing tools that are grounded in real farm contexts - tools that amplify farmers' agency rather than override it. Farmers do not need systems that automate their roles or override their judgment. They need technologies that amplify their agency, reduce stress, and support their ability to learn, adapt, and evolve. In short, they need tools that serve them, not the other way around.

There is enormous potential, but only if we abandon the techno-solutionist mindset that has failed us. If we simply replace subsidy dependence with technological and cognitive dependence on precision farming tools, we will repeat the same mistakes under a different name. True innovation means creating systems that are empowering by design - technologies that are adaptable, affordable, and free of hidden costs or constraints. Only then will we earn the trust of a farming community too often excluded from the benefits of innovation.

One major obstacle remains: many small farms still underestimate the value of field data. That must change. Technologies must offer more than abstract promises - they must deliver immediate, visible benefits. Flexibility is key. Farmers must be free to explore this new field of opportunity at their own pace. At the same time, the technology must offer direct and convincing returns. The appetite for innovation exists. With thoughtful, inclusive design, we can lower the barriers to adoption and create technologies that truly scale, not through imposition, but through actual relevance.

To break this flawed cycle, we must shift precision agriculture away from serving consolidation and toward enabling a new vision - a future of autonomous, resilient small farms.

Figure 55: Stewards and Beneficiaries of Their Land (Aritao, n.d.)

3.1.2. Problem Statement and Vision Statement

This research brings together valuable insights from a literature review, expert interviews, and a quantitative survey, all aimed at distilling a complex issue into a clear and focused problem statement.

At its core, design is all about problem-solving, and valuable solutions emerge from a thorough understanding of the underlying issues. Expressing this central challenge accurately is a vital first step in creating meaningful design impact. Below is the refined problem statement, which lays the foundation for a clear and actionable vision statement.

Problem Statement

*"**European small-scale farms are disappearing** due to a complex mix of challenges, including economic pressures, labour shortages, regulatory burdens, and the loss of traditional knowledge - further exacerbated by climate change.*

***This crisis is driving agriculture toward large-scale, unsustainable industrial models** that compromise ecosystem health and biodiversity, deepening the difficulties small-scale farms face.*

***While PATs have significant potential to address these challenges**, most existing solutions remain anchored in techno-optimism and are designed primarily for large-scale systems, **lacking the farmer-centric focus essential for diverse, small-scale farms.**"*

Vision Statement

*"I aspire to a **farmer-focused tool** that enhances efficiency, effectiveness, and knowledge - keeping farmers at the heart of the system.*

*Through a **modular design that can adapt to their needs**, it empowers them to meet challenges independently and sustainably, **ensuring they thrive as both stewards and beneficiaries of their land.**"*

3.1.2. List of Findings

The key research findings have been summarised in the following list to support the design process.
This summary also serves as the foundation for the subsequent list of requirements.

Small farms are indispensable pillars of sustainable, ecosystem-friendly agriculture and must be sustained.

1. Small farms are vital for securing the future of agriculture.
- 1.1. *Small farms are indispensable for preserving ecosystems.*
- 1.2. *Small farms are more sustainable than large farms, even when both are certified organic.*

2. Most farms in Europe are small farms
- 2.1. *Three out of four farms cultivate crops; only one out of four specialises in livestock.*
- 2.2. *Two-thirds of all farms in the EU are smaller than five hectares.*

3. Small farms cultivate a diverse set of crops.
- 3.1. *Crop diversification enhances resilience, overall yield, and sustainability.*
- 3.2. *Small farms often engage in direct marketing to consumers.*
- 3.3. *The greater the diversity of crops, the more likely a farm is to adopt a two-wheel tractor.*

4. Mechanisation on small farms is challenging because it often limits operational flexibility.
- 4.1. *Two-wheel tractors—and their accompanying implements—are highly cost-effective.*
- 4.2. *The two-wheel tractor market is rapidly growing, especially in the electric-powered segment.*

Small farms face a web of pressures that threaten their survival and demand transformative solutions.

5. Despite their importance, small farms are vanishing alarmingly.

6. Small farms contend with a network of interconnected challenges that make any single intervention insufficient.

7. High manual workloads—particularly weeding—burden small-scale operations.
- 7.1. *Climate change is expected to intensify pest and disease outbreaks through higher temperatures and humidity.*
- 7.2. *EU regulations restricting pesticides will increase manual and mechanical weed control demand.*

8. Many small farms depend on subsidies for their very survival.

9. Agriculture requires systemic transformation, not merely incremental interventions.

Precision agriculture technologies (PATs) hold great promise for small farms and can help make this farming model viable again, but they also carry significant risks.

10. PATs have tremendous potential to help small farms flourish.

11. Farmers generally view PATs positively, yet perceived drawbacks often overshadow perceived benefits.

12. Farmers are open to collaborating with robots, envisioning them as helpful partners.

13. The farmer must remain the ultimate decision-maker at the system's heart.
- 13.1. *Farmers must retain complete control over who accesses their field data and how it is used.*
- 13.2. *PATs' adoption can fundamentally reconfigure who holds epistemic authority.*
- 13.3. *Purely mechanical automation does not threaten farmers' autonomy.*

14. Data-driven analysis can shift expertise away from experience-based knowledge, creating new dependencies on technology.

15. PATs are not intrinsically sustainable; their impact depends on farmers' intentions.
- 15.1. *Increased data-driven insights do not automatically yield more sustainable choices.*

16. Without a holistic approach, PATs risk reinforcing existing inefficiencies rather than transforming agriculture.

Data-driven insights are underestimated yet hold great potential for continuous learning, knowledge retention, and decision making.

17. Data-driven insights are underestimated because links between data-enhanced crop management and outcomes are unclear.
- 17.1. *The benefits of data collection must be better illustrated to make the impacts more tangible and convincing.*

18. Small farms often lack the time, technical expertise, or capacity to integrate data insights into workflows.

19. Data collection can help "train the eye" of farmers, fostering sound judgment, especially during transition
- 19.1. *Data gathering can promote continuous learning by providing unbiased evaluations of field conditions and past decisions.*

20. Excessive dependence on digital tools can lead to a gradual decline in traditional knowledge.

21. Farmers still rely primarily on personal expertise and advice from peers and experts.
- 21.1. *Currently, collected data plays only a minor role in decision-making.*
- 21.2. *Traditional, manual methods dominate field data collection.*

22. The demand for reporting in agriculture is increasing.
- 22.1. *Reducing administrative burdens is crucial to creating a favourable regulatory environment for small farms.*
- 22.2. *Automating compliance and traceability records can significantly decrease administrative workload.*
- 22.3. *Automated record-keeping eases access to climate-smart subsidies and carbon credit revenues.*

Integrated environmental monitoring—combining sensors and bioindicators—is the key to holistic ecosystem assessment.

23. Bioindicators can be used for holistic ecosystem estimation.
- 23.1. *A hierarchical, species-informed approach enhances environmental monitoring's efficiency and alignment with natural processes.*
- 23.2. *Spatial and temporal biases in bioindicator use can be easily avoided.*
- 23.3. *Reliance solely on biological indicators is often infeasible in heavily degraded ecosystems.*
- 23.4. *Only one in four farmers gathers information about biodiversity.*

24. An integrated approach melding visual and auditory sensor technologies with plant parameters and bioindicators provides a flexible, scalable framework for future platforms.
- 24.1. *Monitoring strategies should begin with plant-based sensor measurements, with the option to incorporate bioindicators.*
- 24.2. *Sensor choice—considering cost, spatial and spectral resolution, computational demands, operational range, durability, and environmental resilience—heavily influences data quality.*
- 24.3. *Integrating sound analysis into monitoring systems makes ecological assessments more comprehensive.*

25. The fewer data points collected, the greater the need for skilled/advanced interpretation.
- 25.1. *Continuous AI advancements will increase field measurements' informational value and interpretation.*

Adopting PATs on small farms hinges on affordability, peer-to-peer knowledge exchange, and flexible, farmer-centric design.

26. High cost, fear of dependence on technology, and lack of suitable solutions are the main barriers.
- 26.1. *Awareness of technology-investment subsidies enhances the likelihood of investment.*

27. Peer learning is one of the most effective yet underutilised methods for promoting new technologies.
- 27.1. *Farmers trust insights from fellow farmers and experts.*
- 27.2. *Facilitating knowledge exchange among farmers is crucial for encouraging PAT adoption.*

28. Farmers generally welcome sharing and renting, especially within regional cooperatives.
- 28.1. *Farmers should be able to share or rent components, such as sensors, from trusted peers, providing accessible entry points.*

29. Manual-override features reduce technical dependency and build trust.
- 29.1. *Systems must remain operable without internet or GPS access, giving farmers control during critical moments.*

A modular, ground-based vehicle with interchangeable implements is the optimal PAT platform for small farms, delivering unmatched flexibility across diverse tasks.

30. Farmers seek flexible, adaptable systems capable of multiple tasks rather than highly specialized machinery.
- 30.1. *Carrier platforms should accommodate various implements to perform diverse tasks.*
- 30.2. *Weed management is a key feature farmers expect from PATs.*

31. PATs that solely collect data offer too little immediate value for small-scale farms to justify investment.

32. Unmanned ground vehicles offer more functionality and a better fit for small-farm requirements than unmanned aerial vehicles.
- 32.1. *Trees in the field, essential for biodiversity, pose greater challenges for airborne sensing technologies.*
- 32.2. *Minimal turning space is required on small farms to utilise a maximum cropping area.*
- 32.3. *Differential steering suits small farms due to its low complexity, low cost, and tight-space manoeuvrability.*
- 32.4. *Robust safety mechanisms must detect and correct errors before severe damage occurs to enhance trust.*
- 32.5. *UGVs must either be road-legal for travel or compact enough for easy plot-to-plot transport.*
- 32.6. *UGVs offer varied viewing angles compared to the top-down view of UAVs.*
- 32.7. *UGVs encounter fewer regulatory and legal limitations, as they remain on the ground.*

33. Navigation must be robust and fully functional even in low-signal environments.
- 33.1. *GNSS is often integrated with IMUs and wheel encoders to mitigate its flaws.*
- 33.2. *Vision systems are paired with GNSS to enhance robustness.*
- 33.3. *In areas where GNSS reliability is uncertain, vision-based and LiDAR-based methods perform better.*
- 33.4. *RTK correction signals are likely to become cheaper or even free in the future.*
- 33.5. *A 2D LiDAR layer can improve safety by detecting obstacles that cameras might miss.*

34. Separate computing units dedicated to autonomous navigation allow quick, simple sensor swapping.

35. Lightweight machinery extends operational windows, enabling earlier planting and later harvesting.
- 35.1. *Lightweight machines can continue operating when heavier equipment gets stuck or damages soil.*

3.1.3. List of Requirements

Based on the research and the list of findings, a set of requirements has been established. Due to the conceptual aspect of the design and its novelty, not all requirements are defined with strict numerical values. However, this list acts as a foundational guide that can be continuously updated and improved in future redesign efforts. These requirements are categorised into five main areas.

Carrier Platform

RQ. 1	Modular architecture must allow for component replacement.
RQ. 2	Modular architecture must support phased upgrades.
RQ. 3	Modular architecture must support shared/rental ownership models (easy sensor switch).
RQ. 4	Modular architecture must support weed management.
RQ. 5	Adjustable track width between up to at least 75 cm.
RQ. 6	Adjustable ground clearance (min. 70 cm).
RQ. 7	Turning radius ≤ 1.5 m for high manoeuvrability.
RQ. 8	Drive mechanism must allow for manual operation.
RQ. 9	Maximum weight: ≤ 150 kg (including all essential components but excluding payload).
RQ. 10	Ground pressure: ≤ 0.3 kg/cm^2 to minimize soil compaction.
RQ. 11	Payload capacity: ≥ 100 kg.
RQ. 12	Compatible with common non-powered two-wheel tractor-style implements
RQ. 13	Capable of pushing/pulling implements with a force of ≥ 500 N.
RQ. 14	Must be transportable using a standard trailer.
RQ. 15	Electric-powered with a swappable battery (swap time ≤ 5 min).
RQ. 16	Battery capacity: ≥ 2 kWh, ensuring ≥ 4 hours of continuous operation at full load.
RQ. 17	Capable of performing at least three distinct field operations.
RQ. 18	Reliable operation in diverse environmental conditions (-10°C to 50°C, 0–100% humidity).
RQ. 19	Target price: ≤ 30,000€ (excluding implements).

Automation

RQ. 20	Autonomous navigation accuracy: ±2 cm (RTK-based or equivalent).
RQ. 21	Autonomous navigation must be functional in low-connectivity environments
RQ. 22	Must detect and avoid obstacles within a 1.5 m range.
RQ. 23	Emergency stop must be accessible and engaged within ≤ 3 seconds.
RQ. 24	Offline mode operation must be possible in case of signal loss or system failure.
RQ. 25	Must detect tool failures in autonomy mode.

Sensors

RQ. 26	Must measure at least two key crop parameters.
RQ. 27	Ground Sampling Distance (GSD) ≤ 5 mm/pixel for high-resolution data collection.
RQ. 28	Must have a minimum protection rating of IP65
RQ. 29	Must support auditory sensor integration for bioindicator-based ecosystem monitoring.

Farmer-Robot Interaction

RQ. 30	Operable by untrained or minimally trained personnel (≤ 2 hours of training required).
RQ. 31	Module replacement or reconfiguration must take ≤ 5 minutes.
RQ. 32	Design must be clear, well-structured, and allow for independent, on-field repairs.
RQ. 33	Must provide actionable insights and recommendations
RQ. 34	Farmer must retain full ownership and control of all collected data.

Wishes

RQ. 35	Module replacement or reconfiguration must be tool-free.
RQ. 36	Compatible with common powered two-wheel tractor-style implements.
RQ. 37	Compatible with mobile phone as 'first phenotyping sensor'
RQ. 38	Capable of powering implements with an additional motor.
RQ. 39	Collected data helps train farmers' judgment and supports learning.
RQ. 40	Enables automated traceability and compliance reporting to reduce administrative burden.
RQ. 41	Enables easy exporting of logs or reports to facilitate subsidy access.
RQ. 42	Enables peer-to-peer learning, including intuitive UI and support for knowledge sharing.
RQ. 43	Full functionality must be available without cloud connectivity or third-party services.
RQ. 44	Enables cargo transport during fieldwork and harvesting.

Figure 56: Collaboration with Farmers

3.2. Creative Collaboration

Collaboration with experts and stakeholders was integrated at multiple stages of the design process. In particular, the active involvement of farmers was crucial, as they are the primary intended beneficiaries of the development, as previously discussed.

Designing meaningful technology for agriculture calls for more than abstract problem-solving—it requires a grounded, participatory approach that respects the complexity of the farming environment. This chapter presents a series of collaborative activities that helped shape the design direction by weaving together experiential insight from the field with structured ideation in the lab.

Three complementary methods were employed, each targeting specific intents and stakeholders. A visit to the farm De Biesterhof provided an immersive, hands-on experience that enhanced empathy and contextual understanding at the outset of the ideation phase. A farmer roundtable discussion with farmers facilitated open, peer-based dialogue among various agricultural practitioners, allowing for the refinement of the design vision through real-world validation and critique. Finally, a brainwriting session with the Human-Robot Interaction Lab at TU Delft introduced a different expertise—technical, creative, and speculative—through structured ideation aimed at exploring new possibilities without the constraints of immediate practicality.

By integrating insights from farmers, designers, and robotics researchers, this phase of the project ensured that the emerging design was both visionary and viable, rooted in real needs, yet open to innovation. The following sections describe how each collaboration contributed uniquely to the evolution of the concept, helping bridge the gap between human-centred design and agroecological resilience.

3.2.1. Farm Visit

To better understand the daily realities of farmers, a full day of practical work was conducted on a regenerative farm. Howard Koster, a Dutch regenerative farmer and expert in regenerative agriculture and agroecology, provided the chance to engage in daily tasks at De Biesterhof (see Figure 60), a regenerative farm situated in the Netherlands.

Beyond providing practical insights into the lived experiences of farmers, the day also served as a valuable occasion to engage in ongoing discussions with other farmers who were also present and actively involved. These conversations, held alongside physical labour, reinforced the existing knowledge base that had already been developed through nine in-depth expert interviews.

Figure 57: Main Entrance to De Biesterhof

The farm visit did not provide new quantitative data or specific design requirements beyond what was already established, but that was not its primary purpose. The objective was to foster empathy and a deeper understanding. Designers creating technologies for farmers need to have firsthand experience of agricultural daily life. Thus, this experience was intentionally positioned at the start of the ideation phase, acting as contextual "background noise" to guide and shape the overall design process.

Figure 58: Farm Life Experience

Figure 59: Behind the Wheel of a Tractor

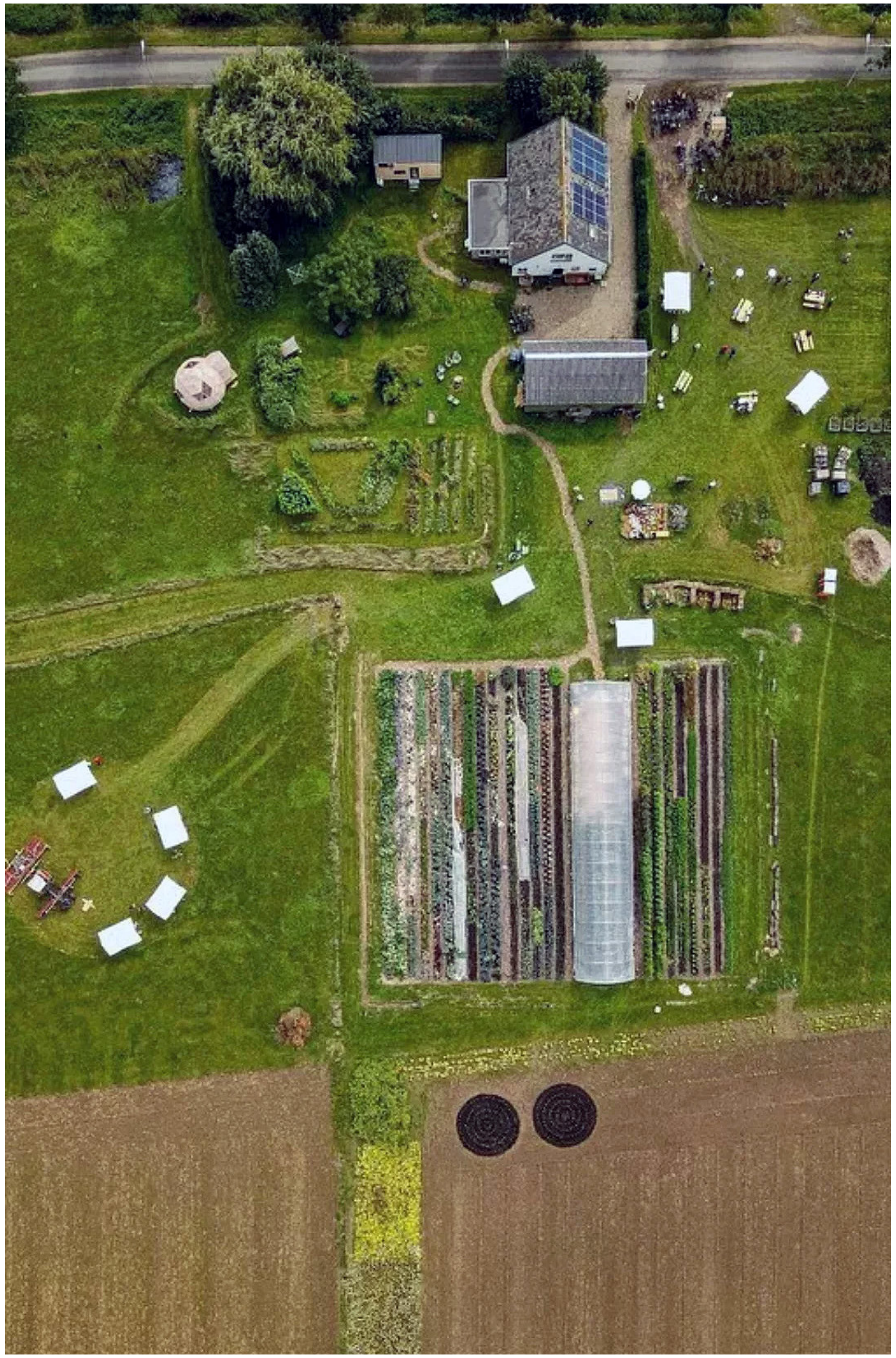


Figure 60: Aerial View of De Biesterhof Farm

3.2.2.Farmer Roundtable Discussion

To validate the proposed design directions and finalise the list of requirements in collaboration with key stakeholders, a group discussion session was held with farmers at Biesterhof, a working farm in the Netherlands. The session took place in the main farmhouse and brought together 14 participants with diverse backgrounds—including experienced farmers, agricultural and environmental specialists, farm advisors, biologists, as well as individuals with limited farming experience who were volunteering on the farm that day (see Figure 61).

Once the design direction was unveiled, the session shifted into an open forum. Farmers were urged to share their views on the advantages and disadvantages, and to engage in collaborative discussions. The designer was not there to defend or advocate for particular ideas. Instead, the focus was on stepping back, minimally intervening while promoting peer dialogue, observing reasoning patterns, and extracting insights from the various arguments and perspectives. Throughout the discussion, elements from the initial requirements list were carefully examined, debated, and refined according to the insights provided. Overall, participants showed strong support for the outlined problem statement, vision, and the suggested design direction: a versatile and adaptable farming robot that enables a gradual shift towards precision farming technologies.

"Especially in the market garden, in the food forests, and the alley cropping system, it would be super helpful—and cool—to have a small, smart machine you can hang appendages on and that can do different stuff."
– Participating Farmer Koster

Alongside the overall view of the design direction, previously identified risks also surfaced during the group discussion. Echoing earlier expert interviews, concerns regarding a potential drop in agronomic knowledge and the fear of increased dependency resurfaced. One farmer articulated this concern as follows:

"If you don't know anything about the plant or the soil anymore, you're just a robot operator. But if the robot doesn't work, how do you know what to pick, when to pick, what to do, what's good soil, what isn't? So, you still would need someone who understands how nature works."
– Participating Farmer

"On a small farm, the farmer is the smartest and most capable data-collecting robot around."
– Participating Farmer

Figure 61: The Big Table at De Biesterhof Farm

Figure 62: A Dialogue Between a Designer and Agricultural Professionals

The weight and dimensions of the device were key topics of discussion. The promise of small, autonomous machines was broadly acknowledged, particularly in relation to future uses in swarm robotics. Lightweight equipment was deemed beneficial and crucial, especially for small-scale agriculture. This demand is anticipated to grow even more important in the coming years, as highlighted by one farmer:

"It´s a really good point ... or it's a really important design direction, to have something much lighter than a tractor, because a lot of our problems last year were really because this damn tractor is just too heavy and can't go on the field. And we'll probably experience many more really, really wet years because of climate change."
– Participating Farmer

An important point that emerged during the discussion was the integration of different systems. While a tool designed for small-scale farming must offer maximum flexibility, this should never come at the expense of core functionality. A "jack-of-all-trades" approach was deemed unacceptable by the participants. The consensus was clear: it is better for the tool to perform fewer functions, but to execute each one with excellence. Careful consideration is therefore needed to determine the appropriate level of modularity and to find the optimal balance between a dedicated device and a highly flexible, multi-functional system. The success of the design depends on delivering consistent quality across all module configurations. One critical factor is how easily and intuitively the system allows users to switch between different modes or functions. One farmer summarized this perspective during the discussion as follows:

"I have a woodworking device, the Emco-Star. It's a table saw, a bandsaw, and a jigsaw. You can do all kinds of things. Almost decent. But as soon as it's a jack-of-all-trades, it's almost always a master of none. And it's really hard to set it up every time. ... That's my experience with non-dedicated devices. Switching functions takes a long time. And time is, of course, money."
– Participating Farmer

In addition to the existing set of requirements, the group discussion led to the identification of two further user-driven needs:

RQ. 31: Module replacement or reconfiguration must take ≤ 5 minutes.
RQ. 35: Module replacement or reconfiguration must be tool-free.

3.2.3.Brainwriting Session (Human-Robot Interaction Lab)

To gain deeper insights and explore innovative design directions, a brainwriting session was held with the Human-Robot Interaction Lab at TU Delft (see Figure 63). The session adhered to the framework as described by Heijne & Van Der Meer (2019), employing the Brainwriting 6-3-5 method. This method involves six participants, each generating three ideas in five minutes per round. Consequently, 108 ideas are produced within 30 minutes (6 participants × 3 ideas × 6 rounds) (see Figure 64).

The fundamental idea of this approach is to circulate written or sketched thoughts after every round. This enables participants to enhance and develop one another's ideas. To steer the ideation process, the facilitator presented a new topic at the start of each round, immediately after participants passed their page to the next person. This topic acted as the focal point for that round.

One of the key benefits of this design method was the diversity and depth of ideas it generated, ranging from visionary, holistic concepts (e.g., a pet-like robotic companion that supports the farmer) to specific design improvements for existing products (e.g., vibration feedback in the handle of a two-wheel tractor). This broad spectrum of abstraction added significant value to the session. On one end, small, concrete ideas offer immediate potential for implementation and testing. On the other hand, comprehensive, system-level concepts encourage a shift in perspective, challenge established assumptions and support a broader reframing of the design space.

Among the many valuable ideas generated, a few stood out during the analysis due to their clarity or relevance to key themes. The notion of modularity, for instance, was illustrated through the "Mr. Potato Head" metaphor and supported by references such as Phonebloks and the Original GARDENA System, offering strong analogies for designing flexible and reconfigurable systems. Another notable direction involved rethinking the wheel, not just as a mobility element, but as a multifunctional interface with the ground, potentially serving additional roles. The integration of digital twins or digital shadows also emerged as a promising approach for enhancing system intelligence and enabling more adaptive, data-driven functionalities.

Figure 63: Brainwriting with the Human-Robot Interaction Lab

Figure 64: The Full Set of 108 Ideas

Figure 65: Ideas Taking Shape on the Sketchwall

3.3. Ideation and Concept Generation

This chapter describes the development process that resulted in the final design. It systematically breaks down each step, offering a clear understanding of how the design evolved.

3.3.1. Ideation and Concept Development

The ideation process began with the list of requirements as a foundational reference. From there, the scope was deliberately expanded to encourage open-ended and unbiased idea generation. Numerous initial sketches developed naturally during the research phase, driven by spontaneous thoughts and insights. Considering the detailed and specific nature of the requirements, the central reasoning that guided the ideation process can be summarised as follows:

Designing a farm robot that empowers farmers to carry out a range of tasks while seamlessly switching between different modes of operation. To lower the barrier to entry, the initial configuration should feel familiar, like a two-wheel tractor that can be operated manually, while offering from the outset the option to upgrade to autonomy for those interested. This upgrade path needed to be fluid in both directions, allowing the farmer to move from manual to autonomous and back without friction.

It would also benefit compatibility with existing tools, allowing farmers to keep their current implements. At the same time, it was essential to introduce pathways into more advanced capabilities, such as mounting sensors for field data collection. This introduced a core design challenge: the machine needed to be compact and stable for transport and implement work, yet capable of high ground clearance for crop scouting, even when plants are tall, requiring a mechanism for easily adjusting its ground clearance. Weed management was another integral consideration, achievable through both manual tools attached to the platform, like finger weeders and data-driven, smart field decisions. Ultimately, a guiding thought was how to foster deeper human-machine collaboration, moving beyond the farmer simply operating the machine, toward a model where the farmer and robot function as one, with the farmer almost becoming an extension of the tool itself.

3.3.1.1. Ecosystem Concepting

Following the initial ideation phase, it became evident that the requirements' complexity, particularly in relation to various modules, needed to be distilled into a modular ecosystem. The focus shifted to identifying how the requirements could be met through distinct modules and determining which components would be essential for the foundational platform. To support this, all potential functions and components that could be integrated into the base platform were mapped, roughly sketched, and structured. These elements are based on insights gathered during the research phase as well as ideas that emerged during ideation (see Figure 66).

This work led to the development of the first design concept for the product ecosystem. As an early-stage version, it supports the ongoing design process. The following section provides brief descriptions of each module. While some elements are intuitive based on the research, others, such as „cargo" and „float", gained relevance primarily during the ideation phase, and their inclusion is therefore explained in greater detail.

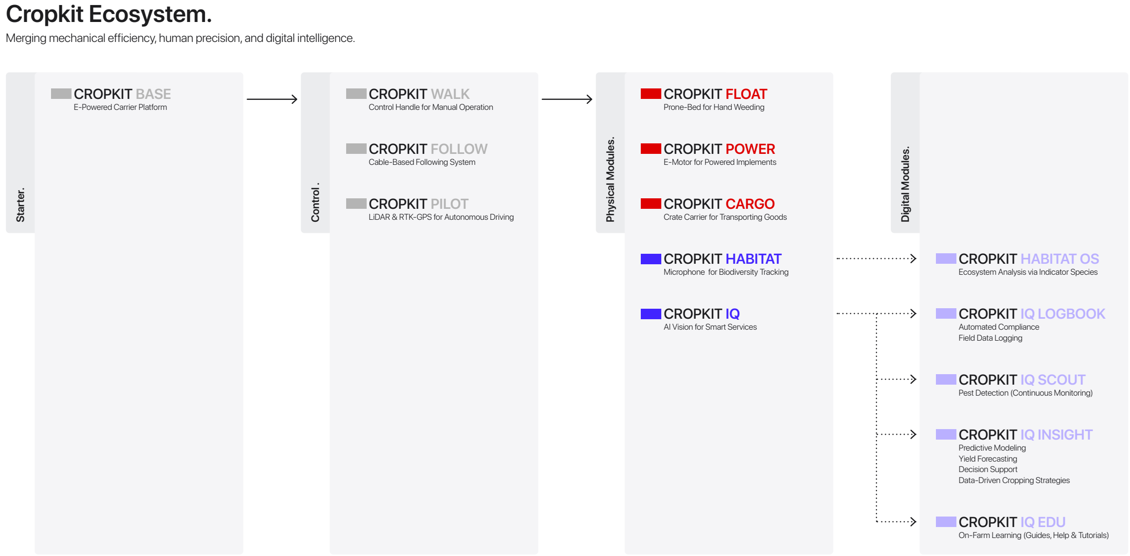


Figure 66: Cropkit Ecosystem - Early Concept

Cropkit Base
The entire concept is built around a mobile base platform. Cropkit Base forms the core of this system, acting as the carrier platform. It must be capable of towing various implements and should include a standard PTO (Power Take-Off) connection to ensure compatibility with commonly available implements on the market. Additionally, height adjustability for the attached implements is essential.

Cropkit Walk
The basic configuration should support manual operation via a handle, drawing on a two-wheel tractor's familiar, well-established principles. A dedicated handle enables direct, hands-on control of the platform.

Cropkit Pilot
This module is intended to enable a transition from manual operation via the handle to fully autonomous driving. To achieve this, the system must be capable of being equipped with an RGB-D camera and RTK-GPS for autonomous navigation.

Cropkit Power
To extend functionality beyond manually or autonomously pulling non-powered implements (e.g., ploughs), an additional module that can drive powered implements (e.g., rotary tillers) using a dedicated electric motor should be considered. While not the primary focus of development, this capability should be accounted for in the concept phase to ensure the technology remains as future-proof as possible.

Cropkit Cargo
To support the transport of boxes and harvested crops, a flat loading surface would be a helpful addition, for example, to place vegetable crates. This feature emerged during the ideation phase but is not part of the core development focus.

Cropkit Float
Effective weed management is a core requirement identified in the research. One solution provided is to use the base platform (either manually or autonomously via the Pilot module). In this configuration, farmers simply attach their weeding implements, like a finger weeder, to the base and perform weeding tasks following existing farming methods.

A proactive strategy focuses on controlling weed growth with intelligent, data-driven cropping systems. By fine-tuning planting strategies, initial weed pressure can be minimised (Lowry & Smith, 2018). The Cropkit IQ module is tailored to facilitate this method (see Paragraph Cropkit IQ). Nonetheless, this strategy requires months or even years to show results and cannot completely eradicate weeds.

As a result, implements like the finger weeder remain essential. Yet, their effectiveness drops near crop stems or in irregular planting patterns, where weeds are often missed. In these areas, farmers still rely on manual weeding, a labour-intensive and time-consuming task. To ease this burden, many turn to prone weeders.

The Prone Weeder
Prone weeders, also known as lay-down weeders, Jäteflieger (Germany), or fietsenwieders (Netherlands), are especially valued on small, organic farms. These battery-powered carts allow operators to lie face down on cushioned platforms and glide over the crops. With both hands free, farmers can weed, thin, or harvest without the strain of bending or kneeling (Coxworth, 2010; Williams, 2017).

Although wheeled creepers have existed for decades, modern prone weeders gained traction in the early 2010s, particularly with electric versions by companies like Andela and FieldWorkers. As interest in non-chemical, regenerative practices grows, these ergonomic tools are making a slow comeback, offering efficient, low-impact weed control. They greatly enhance the speed and ease of manual weeding, reflecting a human-centred, low-impact philosophy. These factors are leading to a gradual renaissance in the popularity of prone weeders (Andela Techniek, n.d.; Farmhack, 2017; FieldWorkers, 2023; Rock et al., n.d.)

Some European growers even prefer simple prone weeders over sophisticated robotic weeding systems. In a 2024 interview, Swiss organic farmer Michael Reichmuth shared his reasons for switching back from robotic weeders to manual, human-operated prone weeders (Eppenberger, 2024):

> ***"Hands and eyes are still more efficient than lasers and sensors from trendy robots. The Jäteflieger is easy to use, free of unnecessary complexity, robust, and meets high ergonomic standards."***
>
> — Michael Reichmuth, Organic Farmer

The prone weeder shows a harmonious partnership between human effort and suitable technology. Instead of being substituted by a costly, overly complicated machine, the farmer is enabled by technology, making them a more efficient tool. Consequently, a prone position module perfectly fits the envisioned design. It allows the farmer to merge effortlessly with the machine, gliding over the fields as one cohesive, efficient entity.

Cropkit IQ
The primary sensor on which all data collection can be based is a visual sensor—an RGB-D camera. The base module must be capable of accommodating this sensor. As identified in the research, measuring bioindicators offers significant advantages. Therefore, an audio sensor module should also be installable.

Figure 67: Designer Engaged at the Sketchwall

3.3.1.2. Concept Selection

During the ideation session, three different design directions gradually emerged, layer by layer (see Figure 69). Despite their differences, they repeatedly featured the same fundamental elements. All three offered manual operation, allowed the user to lie on the device to perform fieldwork by hand, and were suitable for crop scouting thanks to adjustable ground clearance.

To get a rough idea of which concept appeared most promising, a brief Harris profile evaluation was conducted based on the following criteria (see Figure 68). This assessment was quick and approximate, given that all three concepts were still in their early conceptual stages:

Concept A
Concept A featured a tracked system, where different ground clearance levels could be achieved by flipping the body over.

Concept B
Concept B was a differential-steered robot with casters, conceptually similar to a two-wheel tractor. Height adjustment was accomplished by rotating a boom around a pivot point.

Concept C
Concept C took modularity to the extreme, consisting of a single-wheel unit where different modules could be inserted—much like a Lego set—allowing full customization and height adjustment.

Mode Swapping Time – Speed of switching between configurations and ground clearances.
System Complexity – Preference for simple, robust systems for durability and easy maintenance.
Ground Clearance Adjustment – Ease of adapting the height for various tasks.
Ease of Use – Intuitive operation and simple mode changes.
Stability (Manual) – Stability while manually pushed in the field.
Stability (Autonomous) – Stability during autonomous operation, especially with high ground clearance.
Stability (Farmer-On-Top) – Stability when a person lies on top of the device.
Soil Impact – Even weight distribution to minimize soil compaction.

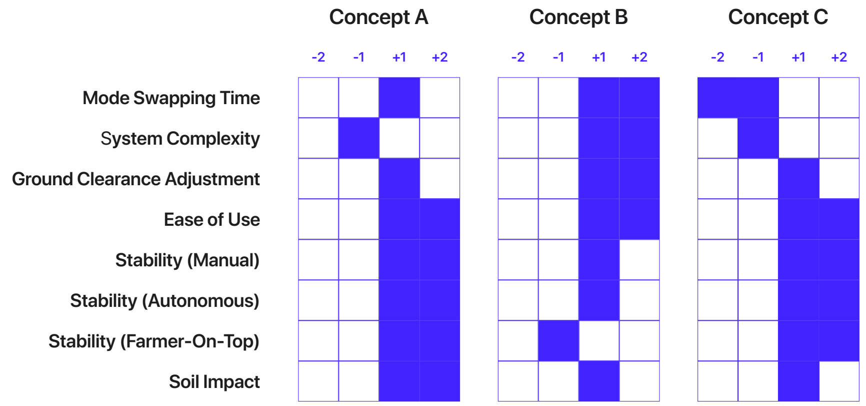


Figure 68: Harris Profile Concept Evaluation

According to the Harris profile, Concept B proved to be the most compelling solution, mainly due to its straightforward height adjustment mechanism and overall simplicity. Although Concept A had benefits in terms of stability and soil impact because of its tracked drive, transitioning between various modes could be challenging, and the tracked system introduces mechanical complexity and higher costs. Meanwhile, Concept C offered the highest flexibility with its significant modularity, yet this advantage resulted in greater complexity. Adjusting the system could consume considerable time and may not be practical, positioning it more as a DIY option rather than a reliable field tool.

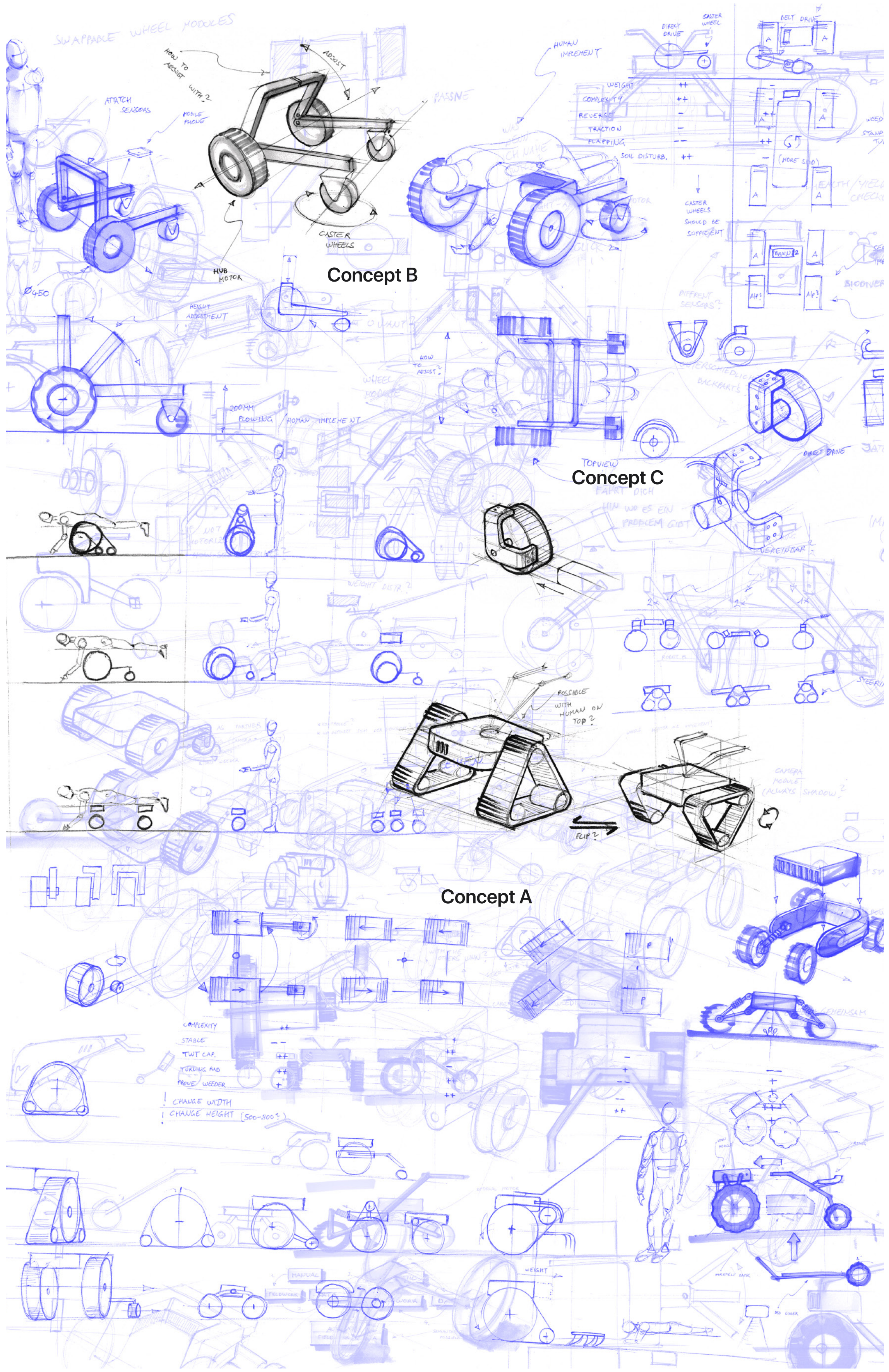
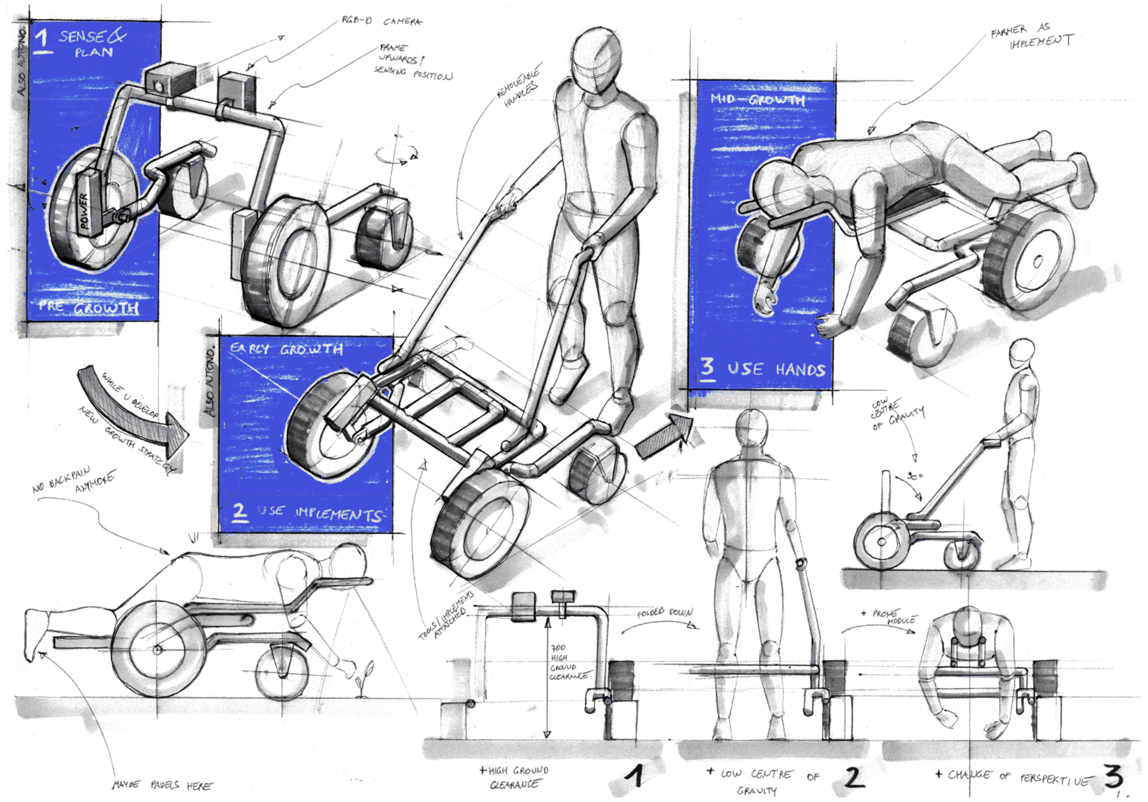
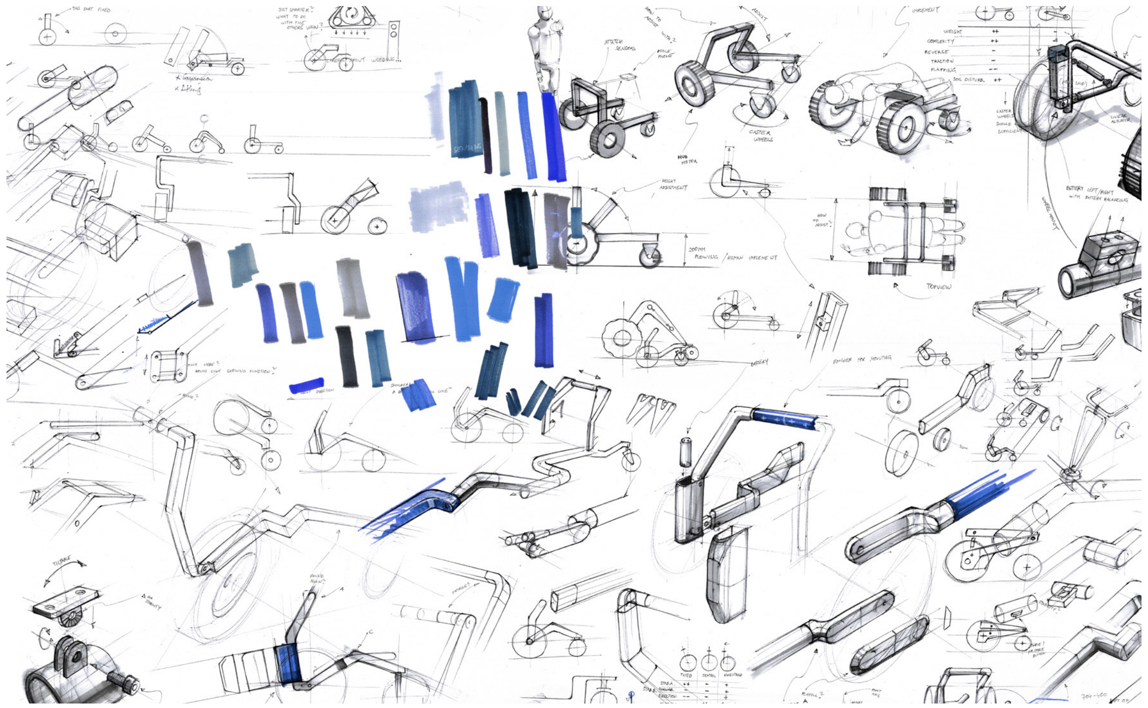


Figure 69: Scans of the First 30 Ideation Pages

3.3.1.3.Concept Refinement

Overall Appearance
Building on the initial concept, the design was further refined into a first key sketch, which visually outlines the various possible stages of the concept (see Figure 70).





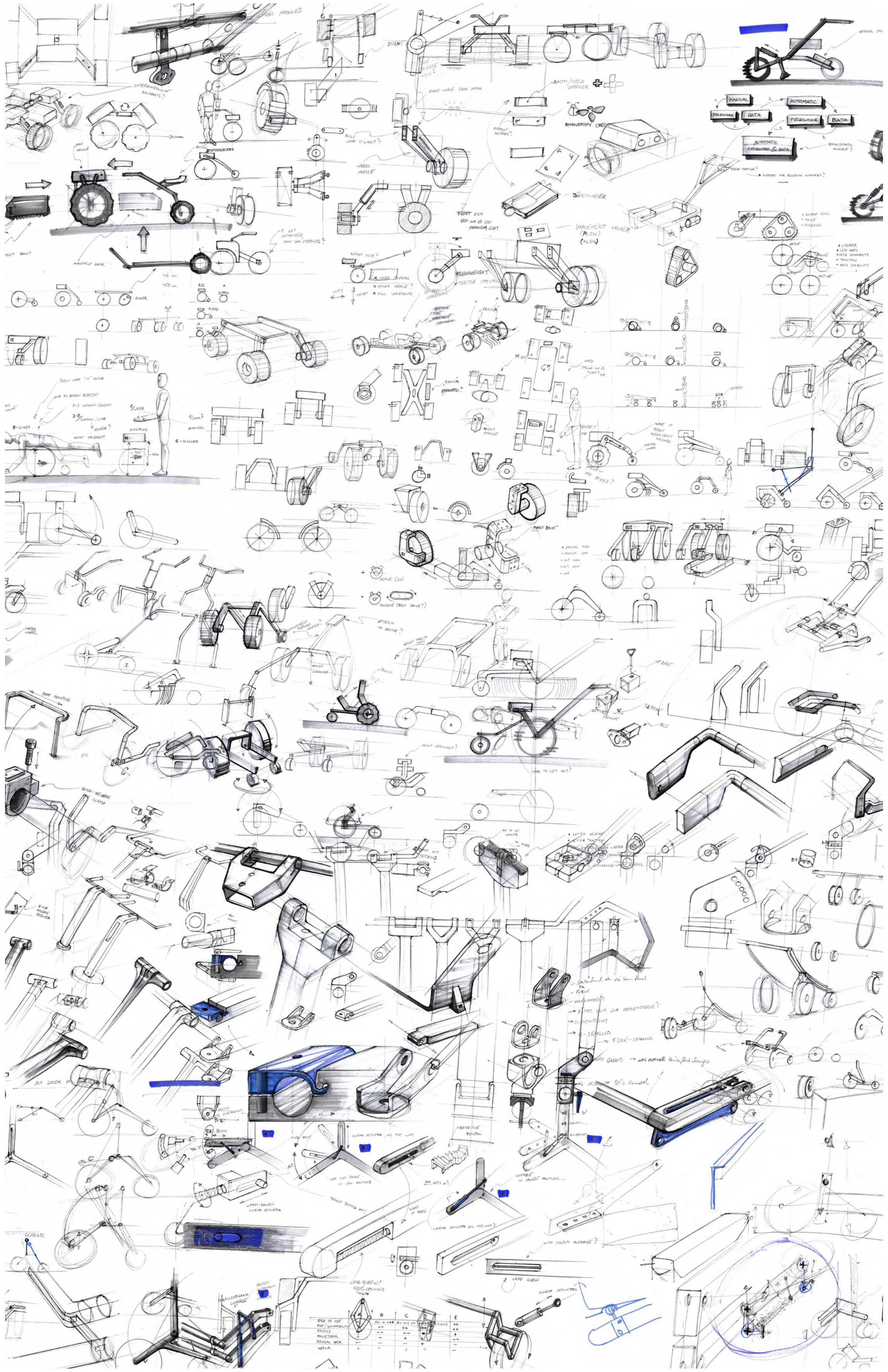


Figure 70: Sketches Concept Refinement

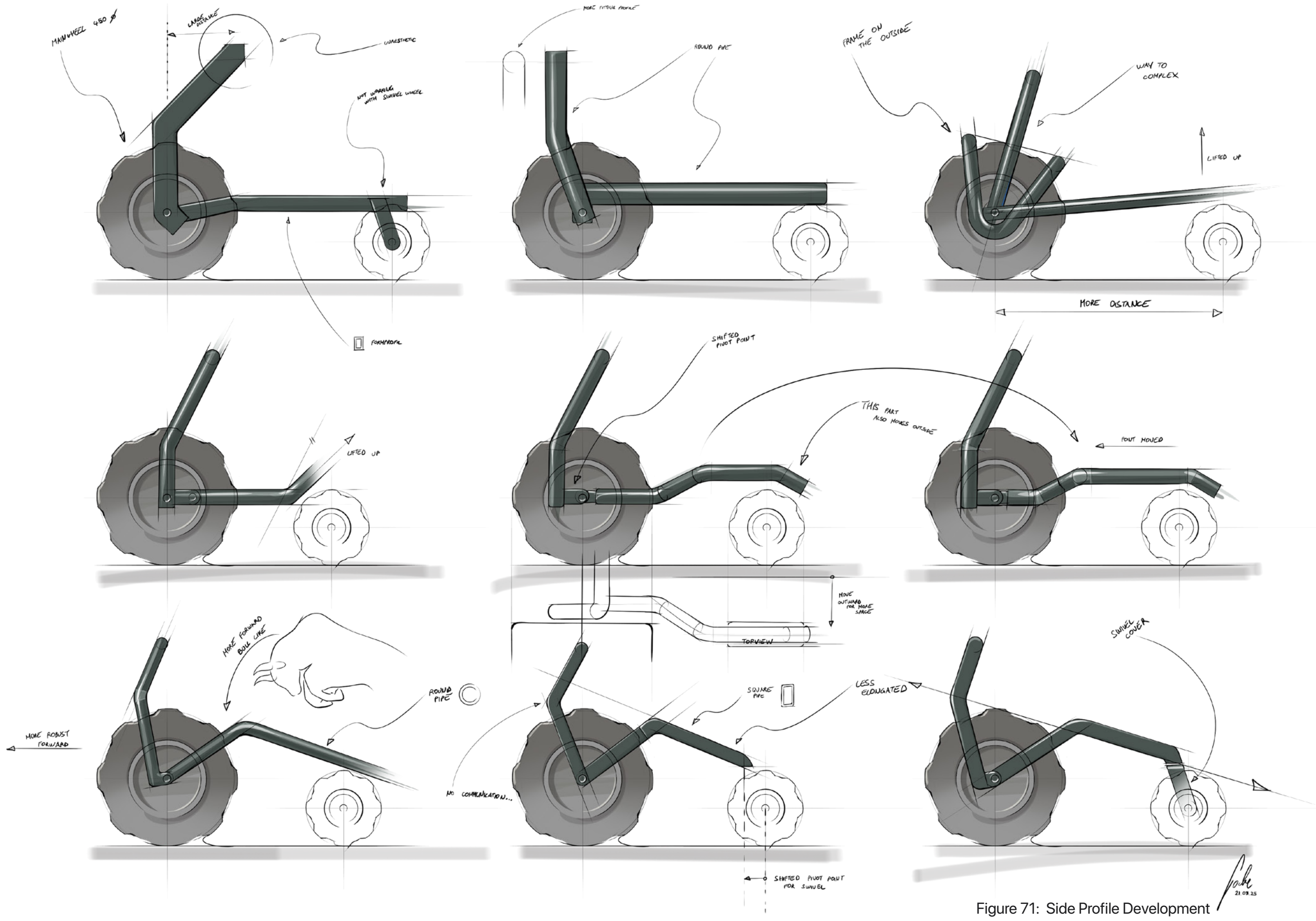


Figure 71: Side Profile Development

Although initially promising, the device first appeared more like a walker than a powerful field tool. To enhance its visual impact and convey a greater sense of strength, the side profile was redesigned. This transformation introduced pronounced "shoulders," inspired by the muscular build of a powerful bull. The overall shape became more angular and robust, emphasizing its commanding presence (see Figure 71).

When folded up, the frame should maintain high ground clearance to allow sensors to be mounted at a sufficient distance above the crops (see Figure 72).

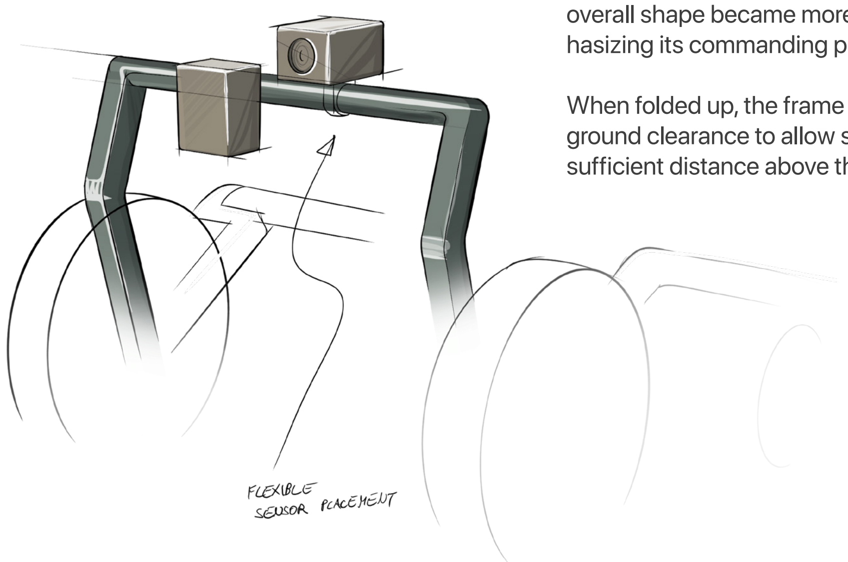
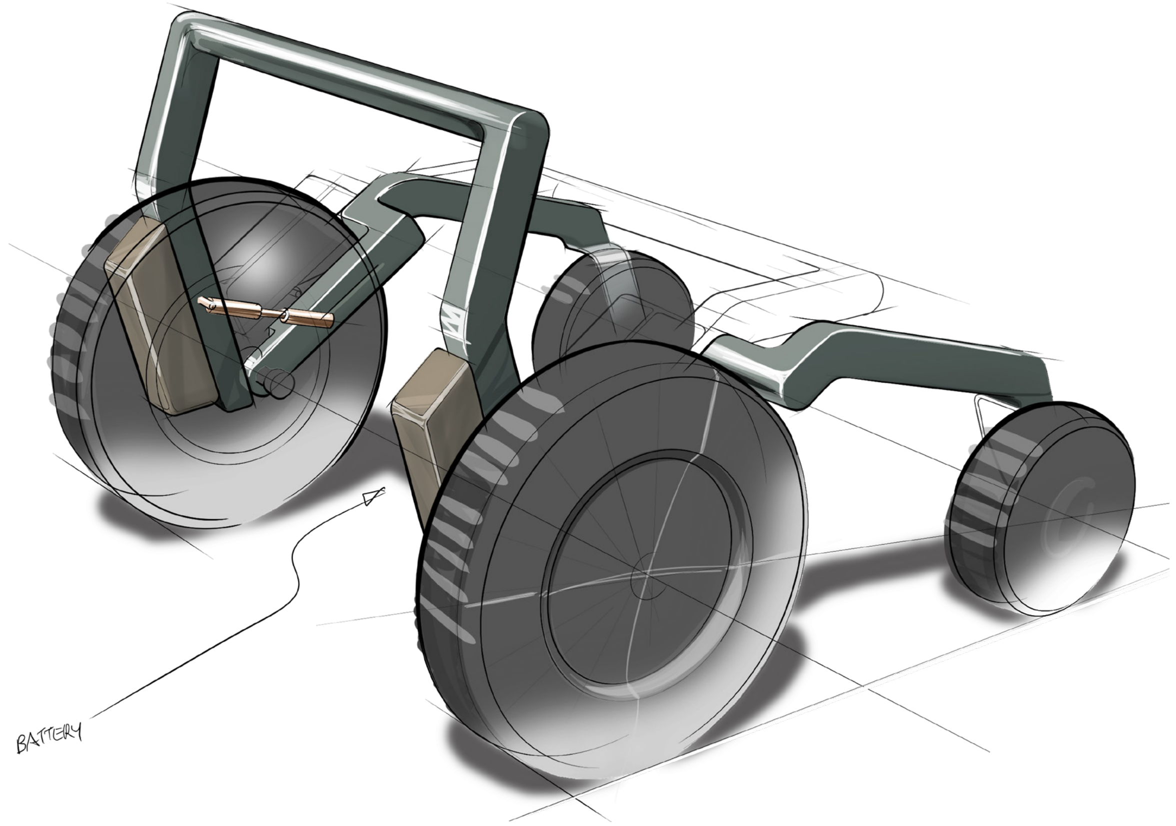


Figure 72: Folded Up Mechanism



At the same time, the handle design evolved into a more delicate and refined form, still sturdy enough to avoid appearing fragile. This handle was intentionally designed to soften the main body's otherwise dominant, "masculine" aesthetic, lending the device a more balanced and neutral appearance. Visually, it suggests minimal physical effort is needed to operate the device. The powerful core carries out the heavy-duty work, while the user simply guides it with a light "leash", as if effortlessly taming a bull. The design communicates that the device is both strong and easy to control.

Figure 73: Digital Refinement of the Key Sketch

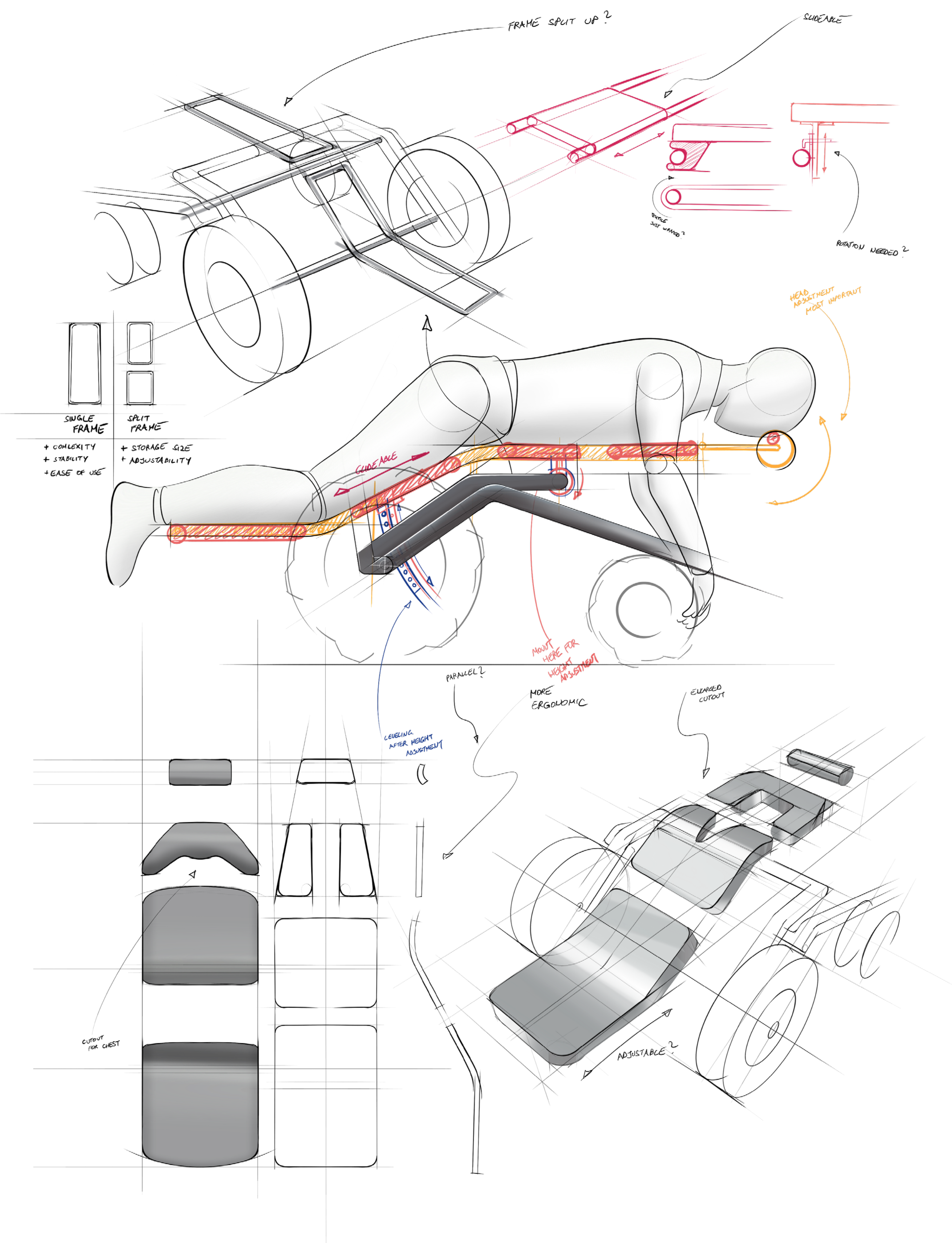


Figure 74: Prone Bed Development

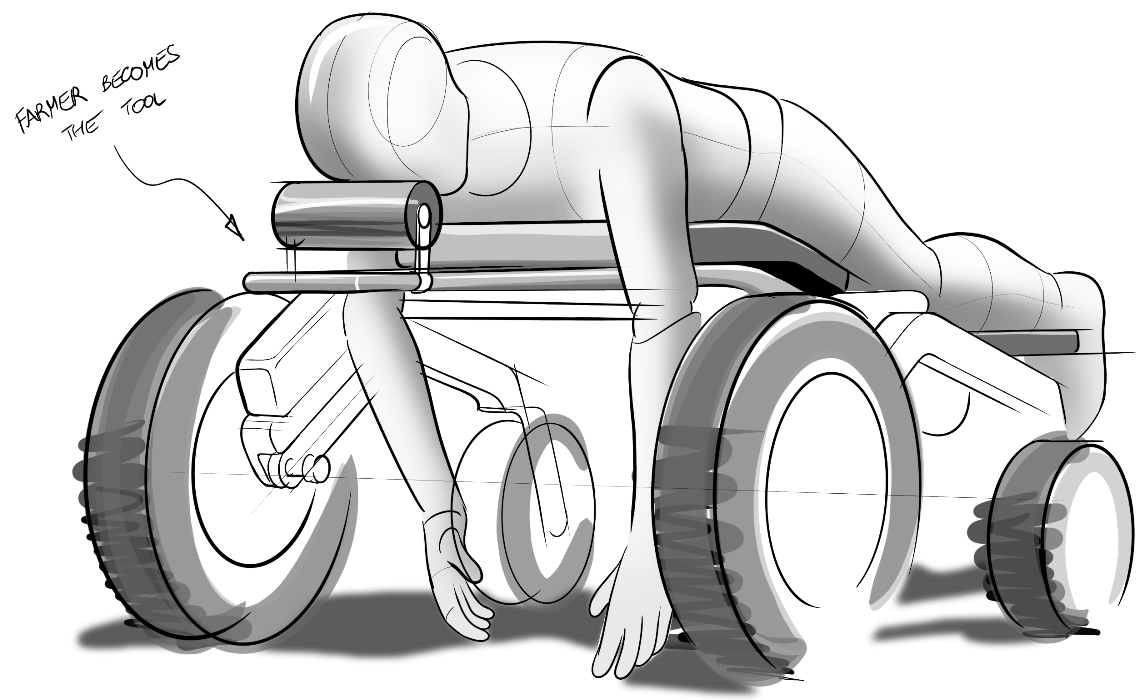


Figure 75: Prone Bed Conceptsketch

Prone Bed Module

Ergonomics is a central consideration in the design of the prone bed module. The surface must allow users to lie comfortably while providing adequate freedom of movement for the arms. The bed's height should also be adjustable to accommodate different working conditions. This adjustment can be implemented via the boom to which the bed is mounted. As the boom is already height-adjustable for agricultural implements and ground clearance, extending this functionality to include positional adjustments for the bed offers a logical and efficient solution.

Existing prone weeding systems were analysed as reference points to inform the ergonomic design. Furthermore, prone positioning systems used in medical settings were studied. These systems are specifically designed to support the head, chest, hips, and legs using pressure-relieving materials. They are optimised for long-duration use by minimising pressure points and the risk of pressure sores. Key pressure zones identified from this research were translated to the prone module to ensure sustained ergonomic support during prolonged operation.

Following the initial sketching phase (see Figure 75), it became evident that a different design tool would be more effective for refining ergonomics and spatial dimensions. Subsequently, virtual reality (VR) sketching was adopted to enhance the design process.

3.3.1.4. Virtual Reality Concept Sketching

Ergonomic considerations and the human figure were pivotal in the design of both the prone module and manual manoeuvring with the handle. Therefore, VR sketching was utilised to address these components effectively (see Figure 76).

By using Gravity Sketch, the design process was significantly improved, allowing for quick exploration and iteration of intricate shapes in an immersive 3D setting. This capability to create and engage with designs at full scale offered a clearer perspective on proportions and spatial dynamics, which is crucial in the initial phases of concept development. This method effectively connected 2D sketches and 3D models, particularly in scenarios involving human interaction.

Digital mannequins at real scale enabled precise ergonomic assessments and spatial analysis, guaranteeing that human-centred design features were integrated from the very beginning.

Figure 76: Design Refinement Using Gravity Sketch

3.3.1.5.Technical Design Refinements

Key design details were refined after several collaborative sessions with engineers and designers at NPK Design. One of the most significant changes was relocating the boom's pivot point. This pivot is the core mechanism that adjusts the ground clearance. It also raises and lowers both the implement and the prone bed. Initially, the pivot point was located at the centre of the wheel axle. For better stability and improved weight distribution, it has now been moved backwards to the "shoulders" of the carrier platform (see A).

Rethinking Height Adjustment

A crucial part of the design is achieving height adjustment and mode switching. Various mechanisms were considered. At first glance, a simple vertical slide might seem most efficient for vertical movement. However, this approach carries a high risk of jamming—especially in open field conditions—if the left and right sides of the robot aren't perfectly parallel. Due to the adjustable ground clearance, installing a crossbar to connect both sides is not feasible (see B).

Though less intuitive, rotational movement offers several advantages. It allows a greater adjustment range (from minimum to maximum ground clearance). While telescopic sliders could reduce the difference, they would also significantly increase the risk of jamming. Therefore, a rotational mechanism proves to be a better solution for height adjustment.

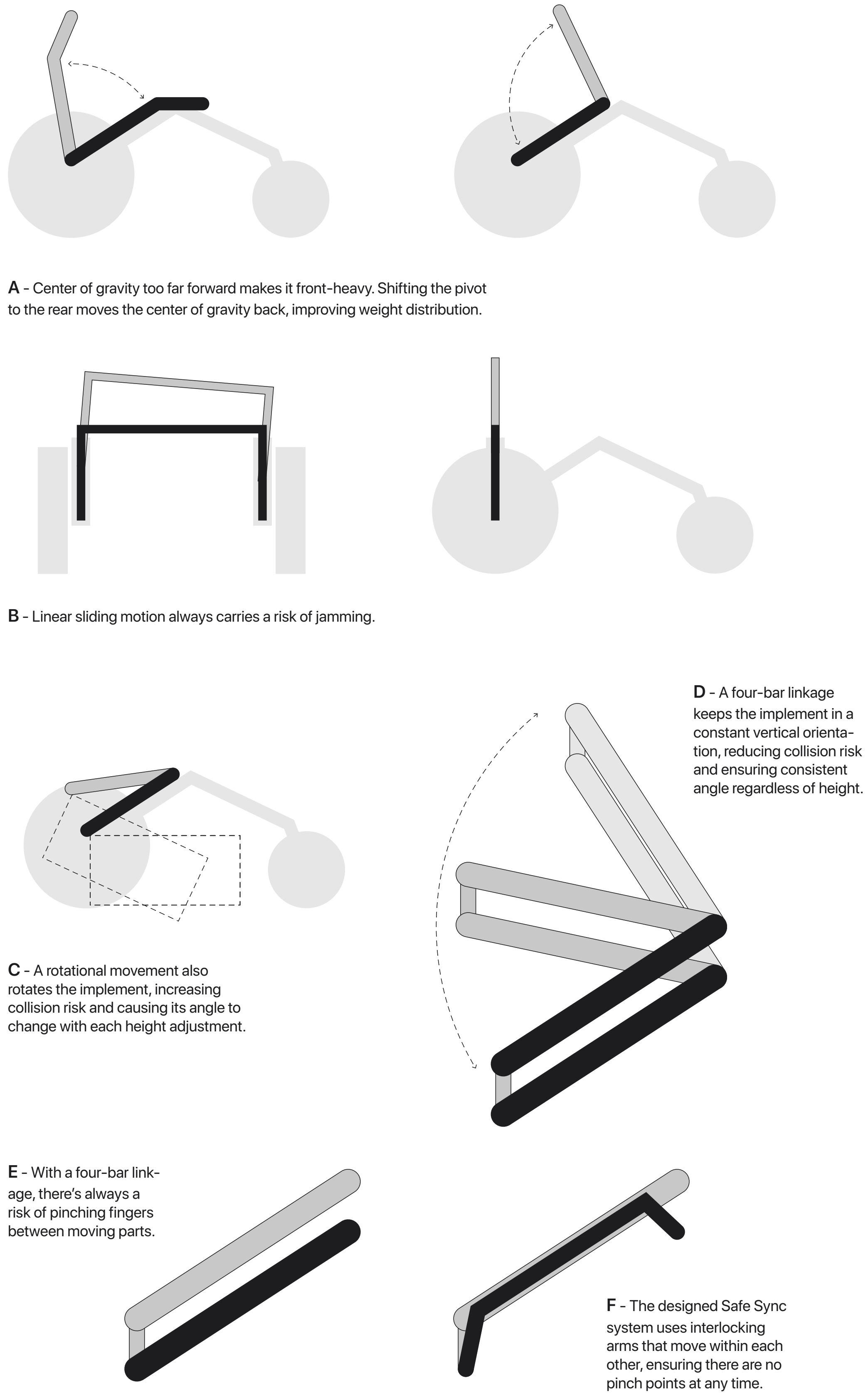
Four-Bar Linkage

While effective, the boom mechanism introduces a new challenge: when an implement is attached, it rotates with the boom as it moves. As a result, any part of the implement extending beyond the pivot point may move downward instead of upward, potentially striking the ground (see C). To address this, the implement must remain level during all height adjustments.

A four-bar parallelogram linkage offers an ideal solution. This mechanism maintains a consistent parallelogram shape by keeping opposing links equal in length and parallel. It comprises two vertical links—the fixed base and the moving coupler—and two horizontal links—the crank and the follower (see D). The follower moves in sync as the crank rotates, ensuring the coupler remains upright and parallel throughout the motion. This configuration keeps the attached implement level and properly oriented during vertical movement.

Despite its effectiveness, the exposed four-bar linkage presents safety concerns. Its scissor-like action creates pinch points between moving parts, particularly between the crank and the follower, posing a risk of injury from fingers or clothing getting caught during operation (see D and E).

To mitigate this, the SafeSync System was developed. This fully enclosed mechanism integrates the four-bar linkage within the structure of the crank (see F). Instead of using an external follower, the parallelogram motion is replicated internally, ensuring the coupler arm stays perfectly vertical. Thus, the crank serves both as a motion driver and a protective housing, shielding users from moving joints and eliminating scissor hazards. The result is a safe, smooth, and synchronized motion mechanism that not only ensures reliable functionality but also features a sleek, modern aesthetic—seamlessly integrating form and function.



A - Center of gravity too far forward makes it front-heavy. Shifting the pivot to the rear moves the center of gravity back, improving weight distribution.

B - Linear sliding motion always carries a risk of jamming.

C - A rotational movement also rotates the implement, increasing collision risk and causing its angle to change with each height adjustment.

D - A four-bar linkage keeps the implement in a constant vertical orientation, reducing collision risk and ensuring consistent angle regardless of height.

E - With a four-bar linkage, there's always a risk of pinching fingers between moving parts.

F - The designed Safe Sync system uses interlocking arms that move within each other, ensuring there are no pinch points at any time.

Figure 77: Explanation of Key Technical Refinements

The design method utilised a hybrid process that integrated traditional sketching, virtual reality (VR), and CAD modelling. Generally, hand-drawn sketches were scanned and transferred into a VR headset, allowing for adjustments and 3D development. These initial VR models were subsequently exported to CAD software such as SolidWorks or Rhino for refinement of dimensions, geometry, and mechanical parts.

After refining in CAD, the models were re-imported into the VR environment to assess their proportions and spatial presence - essentially to "place" the object in space and evaluate the scale's feel. This triangle (see Figure 78) - from hand sketch to VR sketch, then to CAD model and back to VR - was repeated several times, progressively enhancing the design at each stage. The integration of various methods significantly reduced reliance on 3D printing. Although components were occasionally produced through 3D printing, the VR process accelerated many of these stages.

Nevertheless, because VR cannot completely mimic real-world interaction, a full-scale 1:1 prototype was also created and tested with users. This prototyping process is elaborated upon in the next chapter.

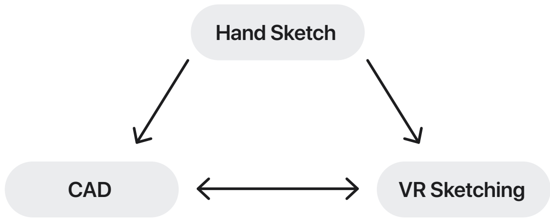


Figure 78: Hybrid Workflow

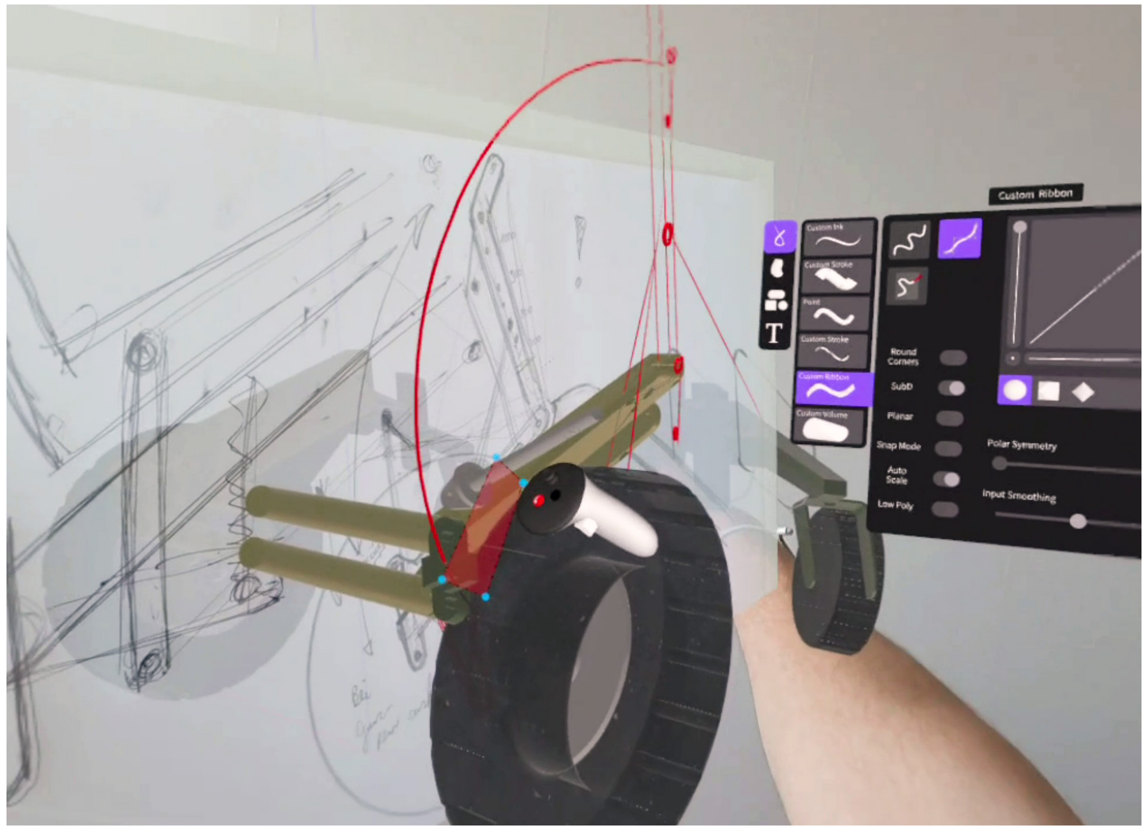


Figure 79: User Perspective Through the VR Headset

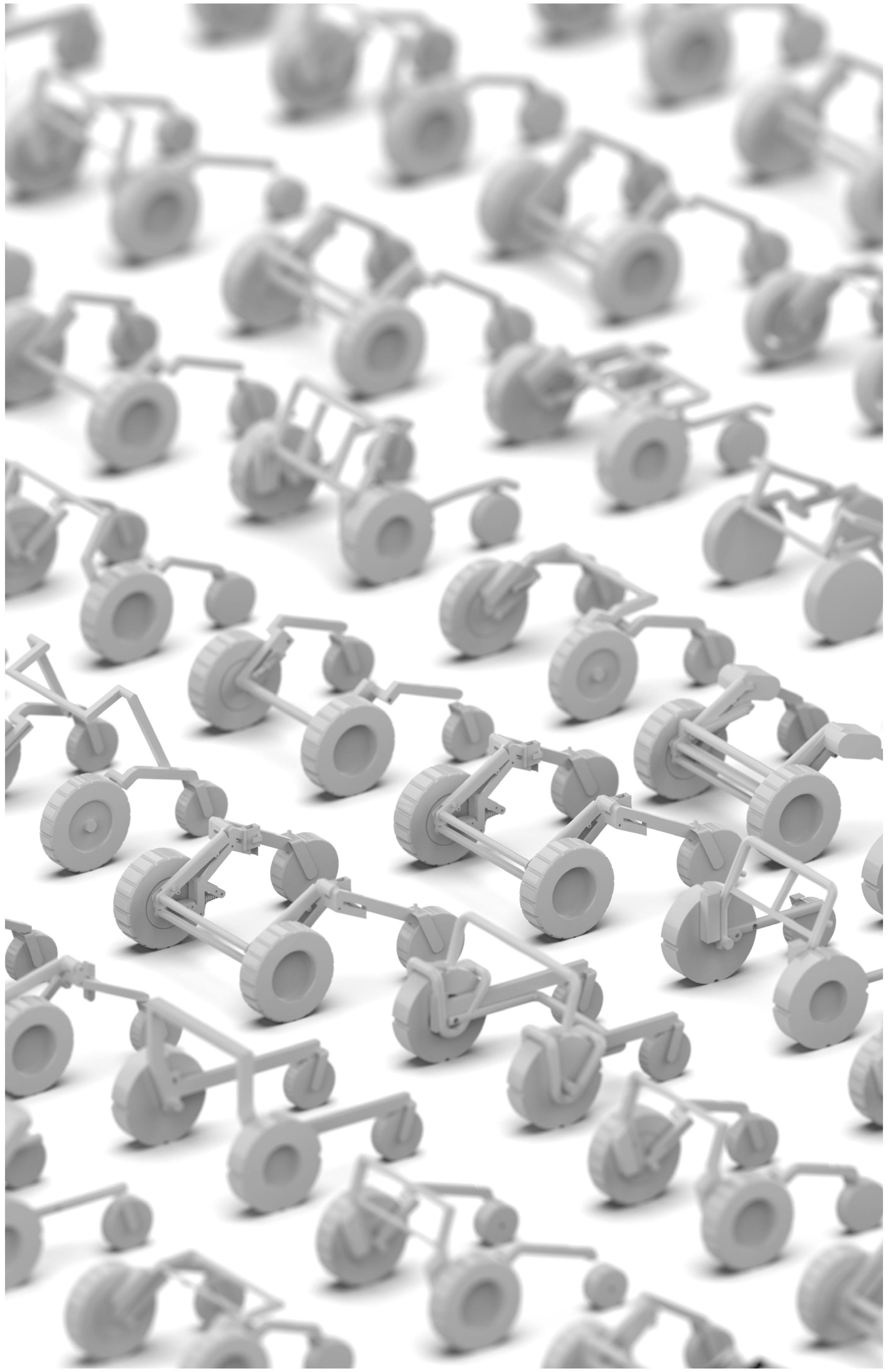


Figure 80: CAD Iterations Snapshot

Figure 81: Prototype Rim Crafted on the Lathe

3.4. Prototyping and User Testing

After further design refinements through VR sketching and early-stage CAD modelling, a full-scale (1:1) prototype was created for user testing.

The Prototype
The full-size prototype was constructed from wood and painted to resemble a metallic finish. It incorporated all key mechanical functions, such as the lever arm, and featured multiple modules. While the prototype offered a basic aesthetic impression, its primary purpose was to evaluate structural stability and construction. Most importantly, it enabled realistic user testing in the field with actual farmers.

The Testing Setup
The testing was conducted outdoors with eight participants, three of whom were farmers. The prototype served multiple purposes throughout the process. Each participant completed four testing scenarios, with the order of modes varied to avoid bias. All tests utilised the Think-Aloud Method—a qualitative research technique in which participants verbalise their thoughts while performing tasks. This method aims to provide insight into their cognitive processes, including reasoning, decision-making, and problem-solving.

The Testing Setup
Testing took place outdoors with eight participants, three of whom were experienced farmers. The prototype served multiple roles during testing. Each participant completed four distinct testing scenarios, with the order of modes randomised to minimise bias. The Think-Aloud Method was employed throughout—a qualitative research technique in which participants verbalise their thoughts while performing tasks, providing insight into their cognitive processes and interaction with the prototype.

Alongside the scheduled user testing, farmers had the chance to assess the design's aesthetics. While the physical prototype focused on functionality, participants could wear a VR headset to experience a more detailed, visually polished digital twin of the design (see Figure 83). This virtual model was overlaid in real-time onto the physical prototype, enabling farmers to interact with the actual object while concurrently viewing the intended final design through the headset.

Figure 82: Stakeholder Dialogue: Engaging with Farmers

Figure 83: Farmers Engaging with VR and the Prototype

Test A (Walk Module):

Setup
To assess the handle's ergonomics and overall controllability, participants were instructed to guide the robot along a predefined 30-meter path in the field, perform a turnaround at the end, and return to the starting point. This test was designed to evaluate the handle position, user comfort, and manoeuvrability of the robot.

Learnings
The robot proved to be extremely easy to control and maneuver. None of the farmers had any difficulty completing the task successfully. Stability was consistently maintained; however, the connection point between the robot and the handle showed signs of significant stress. This issue is not expected in the final model, as it will include motorized assistance - unlike the prototype. Additionally, it was noted that the handle should be shortened by approximately 6 cm.

Figure 84: Cropkit Walk

Figure 85: Cropkit Walk Testing in the Field

Test B (Float Module):

Setup

In this test, the CropKit Float module was mounted onto the robot. Farmers lay on the module while the robot was slowly pulled across the field using ropes. During the movement, they manually removed weeds and grass. The primary objective was to assess the ergonomic comfort of the lying position, as well as to evaluate the structural stability of the system under real working conditions.

Learnings

The test revealed that the preset „standard height" of the bed was too low. It needs to be raised, as farmers frequently had to bend their arms excessively and were unable to let them hang naturally while performing the task. Notably, all participants independently emphasized the overall comfort of the position, indicating that the ergonomics were generally well-suited. However, the footrest should be extended by approximately 10 cm to provide better support.

Figure 86: Cropkit Float Frontview

Figure 87: Cropkit Float Sideview

Figure 90: Cropkit Float in the Field

Figure 89: The farmer's hands are the most precise tools

Figure 88: Looking at the Cropkit Float from the Rear

Test C (Pilot Module):

Setup
For this test, the carrier platform was reconfigured with the CropKit Pilot module. Once placed in the field, the system operated „autonomously," navigating across the area to perform fieldwork. The primary goal of this test was to demonstrate the autonomous functionality to the farmers and observe their reactions.

Learnings
This configuration generated the most uncertainty among participants. Several expressed concerns that the robot might veer off toward the nearby road. Others raised the issue of what would happen in the event of a network failure. For participants who, due to the randomized test sequence, had not yet experienced the manual mode, the handle was introduced and mounted to demonstrate that manual control is always an option.
The handle received overwhelmingly positive feedback. It was almost perceived as a „symbol of authority," reassuring farmers that they could always switch to manual operation if needed. This significantly reduced their sense of dependency on autonomous systems. The cognitive relief provided by the presence of the handle was striking. One farmer summed it up as follows:

„I probably won't even need the handle once this thing runs autonomously, but I'm telling you—just knowing I have it is enough to help me sleep better."

- Participating Farmer

This confirms that the handle - and the ability to take manual control - achieved exactly the intended effect: offering reassurance and promoting trust in the system.

Figure 91: Cropkit Pilot Sideview

Figure 92: Cropkit Pilot alone in the Field (stationary)

Figure 93: Cropkit Pilot Sensor Mounting

Figure 94: Cropkit Pilot Frontview (without Implement)

Test D (IQ Module):

Setup
For this test, the carrier platform was reconfigured with the CropKit Pilot module. After being placed in the field to 'operate independently', farmers received a notification on their smartphones after a short period, informing them that the robot had detected an irregularity in the field and prompting them to inspect the issue more closely.

Learnings
Reactions to the text message notification were mixed. Most participants responded with surprise and some uncertainty about how to interpret or act on the message. It's important to note a limitation of the test setup: the robot remained stationary in the field and did not move, which may have influenced participant perceptions. Notably, older participants appreciated the concept but expressed concern about future generations of farmers. They questioned how well their children would learn traditional farming skills if they were to rely heavily on such systems from the start.

Figure 95: Cropkit IQ - High Ground Clearance

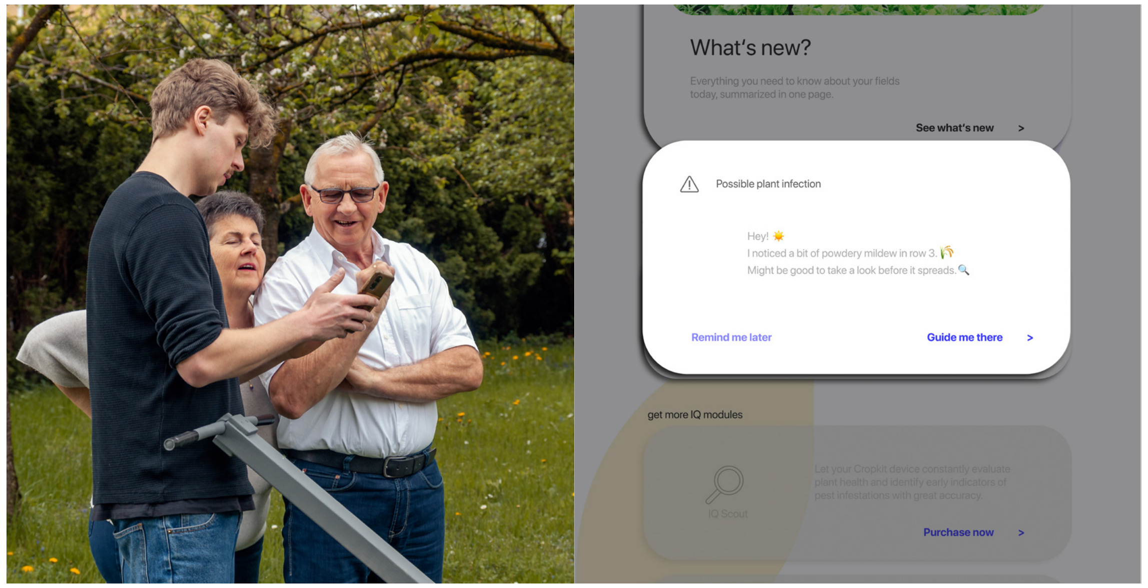


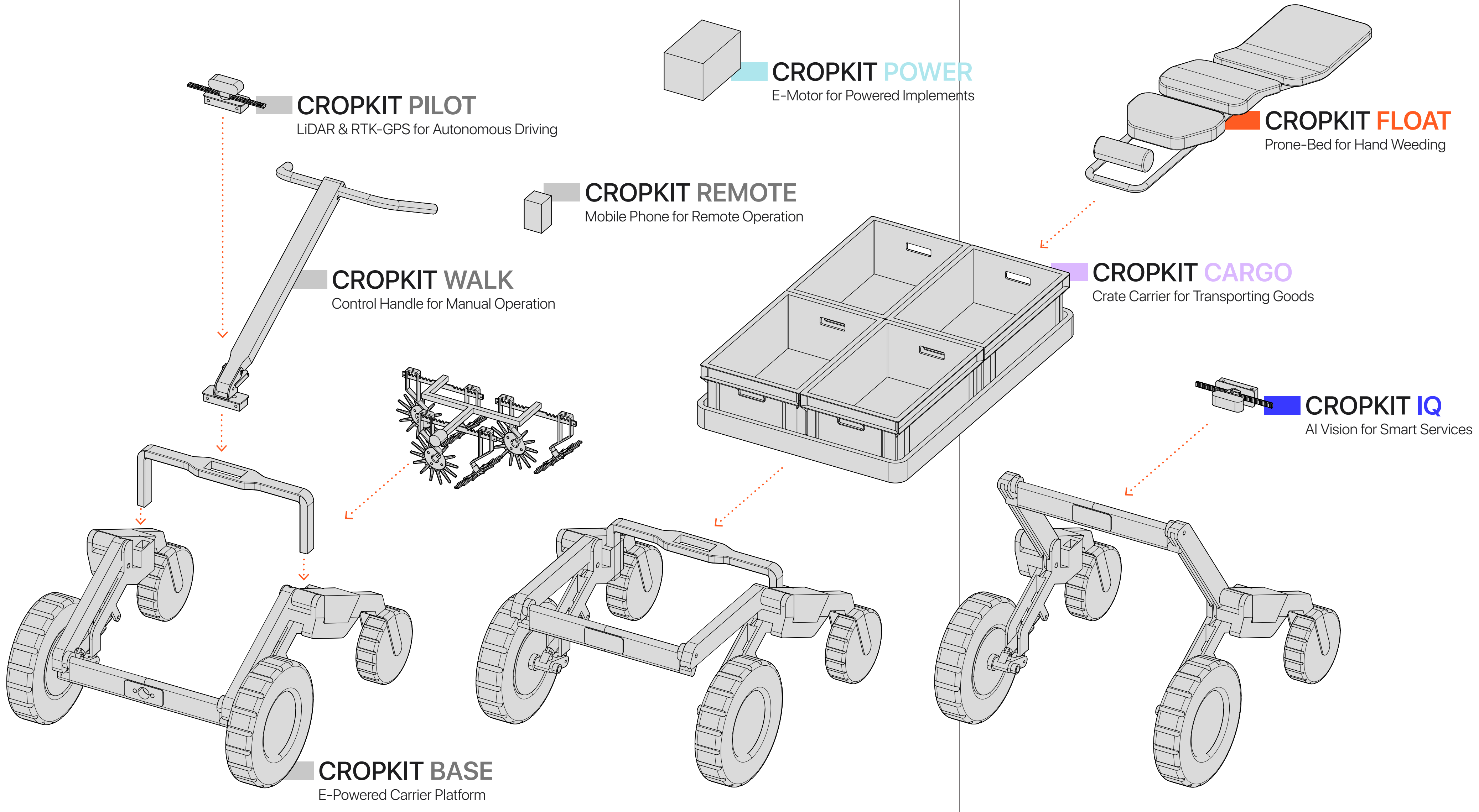
Figure 96: Cropkit IQ – Farmer Receives Notification of a Detection

Figure 97: Cropkit IQ – Four-Lever Mechanism in Raised Position

Overall, the concept showed solid feasibility, viability, and desirability throughout the testing process. While some concerns were raised, these offered constructive insights that will be incorporated into the final design. With only minor adjustments required, the system performed reliably and was generally well-received by participants, indicating strong potential for practical application in the field.

Chapter 4

Final Design



4.1. The Cropkit Ecosystem

This chapter presents the final design concept and system architecture of the CropKit ecosystem. It outlines all the modules included in the final design and discusses both aesthetic and technical design decisions in detail. Furthermore, it provides an overview of materials and costs and addresses the marketing strategy and branding of the final product.

CropKit is more than just a product; it represents a comprehensive ecosystem comprising various components that operate in harmony. These components feature both physical and digital elements, tailored to satisfy users' distinct requirements. Central to this system is the motorised CropKit Base, the lightest and smallest micro-tractor available. It operates similarly to a conventional two-wheel tractor, designed for practical and flexible fieldwork. Users can control the Base using three different methods: CropKit Walk, CropKit Pilot, and CropKit Remote, enabling them to select the most appropriate option for their tasks. Additionally, there are currently four available expansion modules: CropKit Cargo, CropKit Power, CropKit Float, and CropKit IQ. These modules enhance the Base's capabilities, allowing it to adapt to a diverse range of agricultural tasks.

Figure 98: The Cropkit Ecosystem

4.1.1. Cropkit Base.

As its name indicates, the CropKit Base serves as the cornerstone of the entire system. This micro-tractor can be operated manually or autonomously. In its basic configuration, it functions much like a traditional two-wheel tractor, but its design is carefully engineered to accommodate a wide range of future extensions.

Due to its much lighter weight compared to traditional tractors, the CropKit Base can be utilised even under less-than-ideal soil conditions - such as in early spring when the ground remains wet. This feature provides enhanced flexibility in planning field activities and minimises soil compaction. Additionally, its compact design ensures high space efficiency during both operation and storage.

Drive System
The propulsion system features two front wheels, each 450 millimetres in diameter, driven by hub motors, while two heavy-duty caster wheels at the rear enable manual or autonomous differential steering. The front motors are arranged in a cantilevered configuration and operate as direct-drive units. Each motor includes a 45-millimetre stator platform and delivers a continuous torque of 30 to 40 newton-meters, with a peak torque output exceeding 80 newton-meters. These motors are optimized for outdoor conditions and include integrated torque arms.

The direct-drive setup offers several advantages. Because it does not require belts, chains, or gearboxes, it simplifies mechanical construction and reduces maintenance demands. The motors exhibit near-zero rolling resistance when unpowered, allowing for energy-efficient movement. Additionally, the centre of gravity remains exceptionally low since the motor weight is integrated into the wheels. This electric drive system also enables quiet operation, eliminating the need for hearing protection, unlike conventional fuel-powered engines.

Rear Caster Design
The caster wheels at the rear are capable of 360-degree rotation, allowing the robot to move forward and backwards with equal ease. A relatively large pivot offset of 84 millimetres was intentionally chosen to enhance off-road capabilities, where stability and obstacle traversal are critical. The pivot offset—the horizontal distance between the swivel axis and the wheel's point of contact—generates self-aligning torque that helps the caster wheel return to a neutral position after turning or deflecting. The 320-millimetre wheel diameter supports this high offset without sacrificing functionality. The result is improved obstacle negotiation, minimised caster flutter, and greater stability by resisting unintended swivelling. Given that the robot operates at low to moderate speeds, the increased offset enhances control and durability, particularly in autonomous mode, where lane-keeping is essential.

Figure 99: Cropkit Base

Figure 100: Cropkit Base Suspension

Adjustable Ground Clearance with SafeSync System

One of the most essential features of the Cropkit Base is its continuously adjustable ground clearance, made possible by the SafeSync System. Ground clearance ranges from 212 to 832 millimetres and is adjusted using two 24-volt linear actuators, each capable of providing 1000 newtons of continuous force over a 110-millimetre stroke. These actuators are sealed to IP66 standards and equipped with overload protection and a self-locking mechanism, ensuring they maintain their position even without power.

The actuators can be attached at two different positions on the driver link of the four-bar linkage. In the low configuration, they operate from the bottom up to a horizontal lever position, covering a clearance range of 212 to 448 millimetres. This setting is intended for standard applications with implements, the Cropkit Cargo, or the Cropkit Float. To switch to the higher configuration, spring-loaded index plungers on both sides are released, and the actuator connection point is shifted. This adjustment allows the lever arm to operate from the horizontal up to the maximum height of 832 millimetres. The reconfiguration is necessary because linear actuators have a limited stroke. Additionally, this design ensures that the actuators operate at favourable angles across all height settings, improving mechanical efficiency and triangulation for enhanced stability.

This height adjustment affects both the platform's ground clearance and the vertical positioning of attached implements. When tools are mounted, the centre of gravity remains low to ensure stable handling. The same system also allows precise height adjustments for the prone module.

Figure 101: Cropkit Base Invisible Four -Lever - Linkage

Structural Reinforcement and Frame Design
To guarantee structural integrity and off-road performance, several design choices were implemented. The lever arm pivots are notably wide, measuring 140 millimetres, which provides a solid foundation to absorb mechanical loads (see Figure 102). The arm is mounted using a dual-shaft U-bracket configuration, which allows for stable rotation even under lateral forces. The central axis of rotation is 25 millimetres thick, further contributing to the system's rigidity.

A height-adjustable cross brace at the rear connects the left and right flanks of the platform, enhancing overall frame stability (see Figure 103). In high-clearance mode, intended for light-duty tasks such as phenotyping, the cross brace is removed to maximize available space. In low-clearance or heavy-duty modes, the brace is reinstalled to reinforce the frame, particularly when tools are used or when the platform carries a person in float mode.

This cross brace features a custom height adjustment mechanism. First, the safety pin is removed. Then the quick-release skewer, or cam lever, is opened to free the connection. This allows the brace to move freely for repositioning. Integrated spring plungers in the frame ensure even alignment on both sides. Once the desired height is set, the skewer is closed, which automatically aligns the mounting holes vertically through the spring plungers and horizontally through the skewer. The safety pin can then be reinserted without any risk of misalignment. This mechanism, comprising the quick-release skewer, the safety pin, and the spring plungers, ensures smooth and precise adjustment while maintaining both a force-fit and form-fit connection.

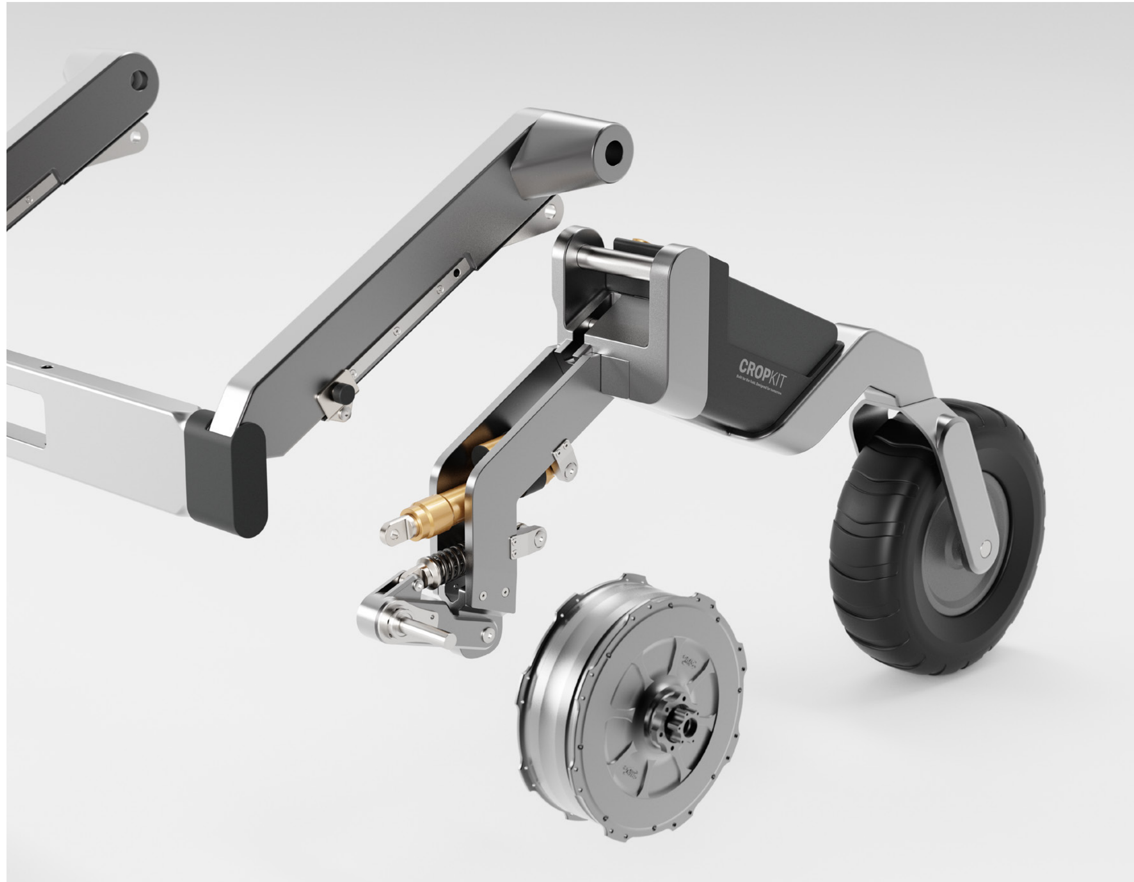


Figure 102: Cropkit Base Lever Arm Pivots

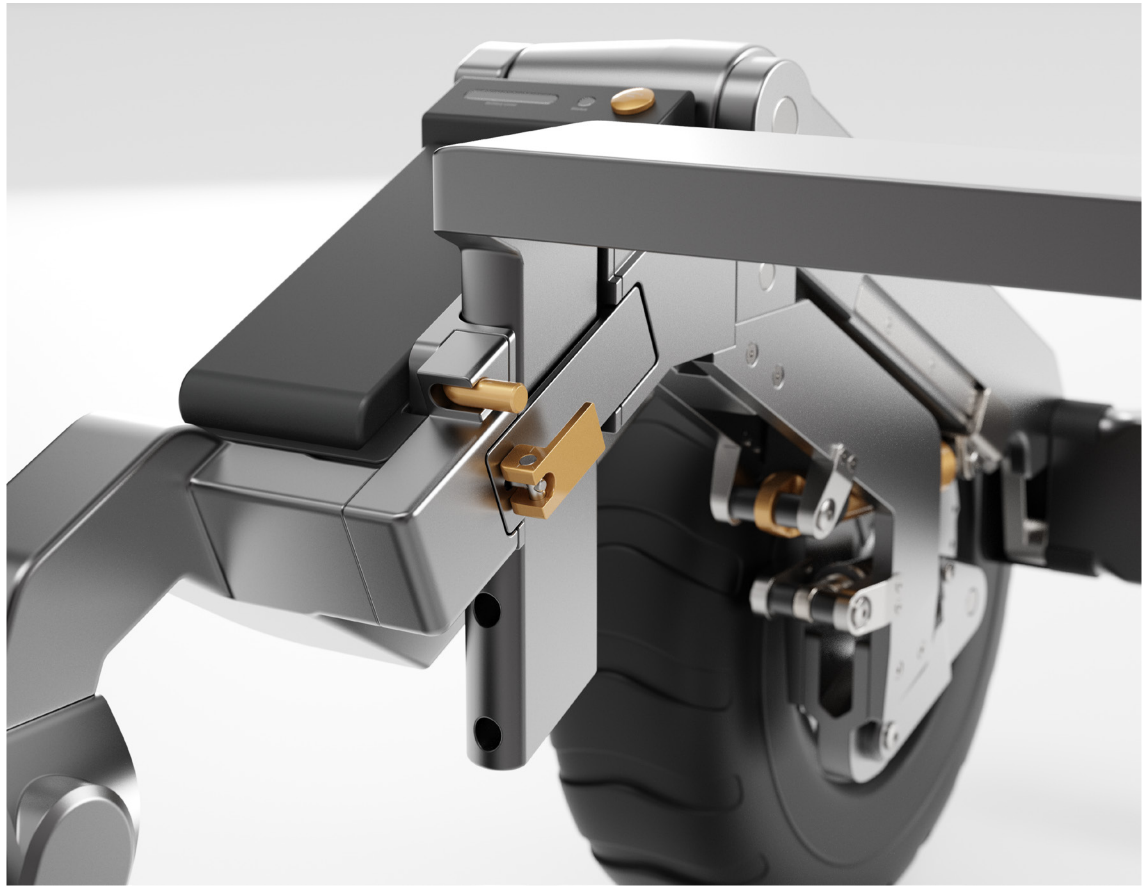


Figure 103: Cropkit Base Brace Adjustment

Physical Interface
Both the height-adjustable front arm and the rear cross brace feature a standardised cutout designed to accommodate interchangeable module inlays. These inlays can be quickly swapped without the need for any tools. To remove or replace a module, users simply pull out the securing pins, after which any compatible module can be inserted thanks to the uniform interface design. This approach not only simplifies usability but also establishes a highly modular and extensible system architecture. The standardised physical interface ensures that future modules—whether developed by Cropkit or third parties—can be seamlessly integrated, reinforcing the system's openness and long-term adaptability.

Energy Supply and Computing Units
The Cropkit Base features a dual-battery system, with one 24-volt battery mounted on each side. This setup provides balanced weight distribution and increases system resilience. If one battery fails, the Battery Management System (BMS) allows the platform to continue operating for a limited time using the remaining battery.

Above the battery compartments are two computing units. The left side houses the central unit responsible for the Cropkit IQ module and all necessary operational intelligence. The right side contains a separate unit dedicated exclusively to autonomous navigation.

User Interface
The user interface on the device itself has been intentionally kept minimal. This design choice ensures that if advanced features requiring a dedicated interface are not used, no unnecessary components are installed. Moreover, a sophisticated digital interface integrated directly into the robot could pose durability issues under rough outdoor conditions such as wind, rain, or dirt. From a sustainability perspective, including a screen in the robot itself would be redundant, considering that most farmers already carry a smartphone in their pocket. For this reason, most interaction with the robot is conducted via a mobile device.

To provide a user-friendly control interface, a microcontroller on the Cropkit Base establishes a local Wi-Fi access point and hosts a lightweight web server. This setup enables users to connect directly to the robot using their smartphones and access a browser-based control dashboard. Because this system operates independently of cellular networks, it offers reliable, low-latency communication even in remote field environments. The result is an intuitive, accessible, and efficient user experience.

Only the most essential information is displayed directly on the Cropkit Base module itself. The current battery level and overall system status are communicated through LED indicators. All other detailed system data is streamed directly to the user's mobile app.

Safety Mechanism
To ensure operational safety at all times, the Cropkit Base features an easily accessible emergency stop mechanism. A red emergency stop button is located on the left side of the platform. Pressing this button instantly cuts power to the drive system and halts all movement of the Base, regardless of whether it is being operated manually or autonomously. This hardwired safety feature is designed for quick intervention, such as in the event of unexpected behaviour. Its prominent position ensures it can be activated with ease, even in stressful situations or while wearing gloves in field conditions.

Figure 104: Cropkit Base User Interface

4.1.2. Cropkit Walk

Cropkit Walk is the first of the three control options available for operating the Cropkit Base. This module connects directly to the base via the standardised interface and is secured using locking pins. Once mounted, it is plugged into the robot's central control unit via a direct cable connection. The ergonomic design and positioning of the handlebar were developed using live-scale VR simulations and later refined through a full-scale physical prototype.

The height of the grip unit is adjustable via the cross brace, allowing users to tailor the handle to their preferred working position. Additionally, the vertical shaft of the handlebar features an integrated ball bearing at its base, enabling full 360-degree rotation. This feature is particularly useful when the operator prefers to walk beside the robot—such as in the tire track—rather than directly behind it, in order to avoid stepping on crops. To reposition the handle laterally, the user pulls out the spring-loaded index plunger, allowing the entire grip column to swivel outward (see Figure 105).

To ensure ergonomic alignment even in the swivelled position, the upper grip bar can also be rotated and adjusted independently. This adjustment is performed by loosening a skewer at the top of the vertical post, rotating the bar to the desired orientation, and then securing it again. Similar to a bicycle handlebar system, this allows fine-tuning of both position and angle. The rotational interface at the top is deliberately designed with an almost square geometry rather than a perfect circle. This makes even slight misalignments visually noticeable, which helps the operator return the handlebar precisely to the neutral 0° position.

The upper grip bar includes two dead-man switches—one on the left and one on the right. The left switch controls the left motor, and the right switch controls the right motor. When both switches are pressed simultaneously, the robot moves straight forward. Releasing either switch immediately deactivates the corresponding motor entirely, causing the robot to turn toward the stopped side. For example, if the left switch is released, the left motor stops, and the robot pivots to the left. This intuitive control method allows the operator to steer the robot with minimal physical effort while

Figure 105: Cropkit Walk

Figure 106: Cropkit Walk Detail

4.1.3. Cropkit Remote

Cropkit Remote is the second control option available for the Cropkit Base. Like the standard user interface for the base, it operates through a local Wi-Fi access point that hosts a lightweight web server. This enables users to connect directly to the robot using a smartphone and control it via a simple, browser-based interface—no additional apps or external network infrastructure are required.

In addition to manual control, Cropkit Remote introduces users to basic autonomous functionality. It features a low-cost autonomy mode called FieldPath Replay Lite, a "teach-and-repeat" system. In this mode, the user manually guides the robot along a desired path or task using the smartphone interface. During this process, the robot records motion data from its wheel encoders and IMU to capture relative movement over time. The robot can later autonomously replay the path by following the same movement sequence.

This approach is highly intuitive and requires no programming skills, making it accessible to non-technical users. However, because it relies only on internal sensors (wheel odometry and IMU), it is subject to limitations. Odometry errors from wheel slippage or uneven terrain and IMU yaw drift can lead to deviations during replay. Although filtering techniques like a complementary filter can help mitigate these effects, the absence of GPS or external corrections means the robot cannot determine its absolute position.

As such, FieldPath Replay Lite is best suited for short, repeatable tasks in fixed or structured environments. Additionally, changes in battery voltage may affect motor performance, further impacting replay accuracy.

Despite these constraints, this mode offers a fast and user-friendly path to basic automation—ideal for early trials, simple routes, and scenarios where ease-of-use is more critical than centimetre-level precision.

4.1.4. Cropkit Pilot

Cropkit Pilot is the third and fully autonomous navigation configuration for the robot, designed for high-precision tasks. It integrates an RTK-capable GNSS antenna for centimetre-level geolocation and a stereo depth camera for 3D visual sensing. The GNSS unit supports real-time correction data, enabling accurate field mapping and path tracking. The stereo camera captures both RGB and depth information, enabling the system to detect terrain features and obstacles in real-time.

Installing the Pilot module is tool-free: the handle is removed and the module connects via a standard interface. The crossbar linkage is raised to improve GNSS signal reception and to ensure the camera remains unobstructed by any attached implements, protecting it from dust and debris. Once mounted, the module also integrates seamlessly with the Cropkit Base's IMU and wheel encoders, enabling accurate positioning even during short GNSS signal losses. Additionally, stereo vision aligned with crop rows provides reliable local navigation, even in the presence of weeds.

The camera is mounted on a Picatinny rail—a robust, standardized mounting system originally developed for military use and now widely adopted across industries. Its precise slot spacing and mechanical strength support a wide range of commercial accessories such as brackets, clamps, and quick-release systems. This modularity ensures easy adjustment of camera positioning and allows for future upgrades and sensor enhancements.

In Pilot mode, the RGB-D camera not only assists with navigation but also serves a critical safety role by monitoring the implement. If the implement deviates from its intended position or threatens to damage crops, the camera can detect the anomaly and initiate appropriate corrective actions.

This mode also supports a more advanced version of the teach-and-repeat system: FieldPath Replay Precision. Unlike the basic version, this enhanced method combines data from wheel encoders, IMU, and RTK-GPS. During the teaching phase, the robot logs high-accuracy GPS waypoints along with motion data. In the replay phase, it uses waypoint tracking algorithms to follow the recorded GPS path, rather than relying solely on relative motion. The RTK-GPS ensures centimeter-level accuracy, enabling the robot to start from any point and still align with the taught route precisely.

FieldPath Replay Precision significantly reduces drift and is ideal for longer routes and real-world field applications where high precision, flexibility, and reliability are essential.

Figure 107: Cropkit Pilot

4.1.5. Cropkit Power

Some implements, like ploughs or planters, are passive and towed or ground-driven. Others, such as mowers, need active components and a separate power source. For those wanting to use powered implements with the Cropkit Base, the Cropkit Power module is offered. This module allows the robot to operate powered attachments through an electric Power Take-Off (PTO) system. It is equipped with a 24-volt brushless DC motor that produces 3 to 5 kilowatts of continuous power. The motor generates high torque at low RPM, making it ideal for heavy-duty tasks. Its operating speed, typically between 1500 and 3000 RPM, is mechanically reduced to the industry-standard 540 RPM using either a belt or chain drive. The module connects easily to the robot's standard interface, with the implement installed on the opposite side.

The motor is currently designed to function with standard implements available in the market. However, it would be beneficial to consider developing implements specifically optimized for Cropkit, either through in-house efforts or by external suppliers. When used with the autonomous Cropkit Pilot, the necessity for large, heavy-duty implements decreases. Traditional implements tend to be oversized to achieve maximum coverage quickly, a model driven by human operation. In contrast, with the robot's autonomous functioning, time is less of a concern. This transition mirrors the transformation seen in lawnmowers: moving from loud, bulky designs to compact, silent robotic mowers that utilise autonomy for a different kind of efficiency. This evolution creates opportunities to design smaller, lighter, and more effective powered implements specifically for the Cropkit platform, better adapted for continuous, autonomous operation in the field.

Figure 108: Cropkit Power

4.1.6. Cropkit Float

The Cropkit Float module creates a genuine partnership between humans and machines. Rather than depending on costly and sophisticated tools, this system transforms the most skilled instrument—the farmer—into the tool itself. Mounted on the Cropkit base, the Float module includes a platform that is ergonomically designed for extended periods of comfortable use. Each support surface consists of EVA foam cushions, which can be easily repositioned and adjusted with plastic clips along the base frame to fit each user perfectly. The platform's height can be continuously adjusted between 540 mm and 640 mm, utilising linear actuators at the front and a height-adjustable cross brace at the rear to keep the platform level during adjustments.

In this float setup, the machine advances steadily and automatically, allowing the operator to focus on their tasks without managing propulsion. The operator lies face down, gaining an unobstructed view of the crops, with their hands entirely free for precise manual activities like weeding or thinning. Steering and speed control are managed through the feet: pressing one pedal slows down that side of the machine, gently directing it where needed, while pressing both pedals at once halts the platform entirely. This straightforward, foot-operated braking system allows for smooth, hands-free navigation, making it ideal for enhancing efficiency and comfort during long hours in the field.

Figure 109: Cropkit Float

Figure 110: Cropkit Float Detail

4.1.7. Cropkit Cargo

Cropkit Cargo is a modular solution designed to support farmers in transporting tools, equipment, or harvested goods—whether in the field or around the farm. The cargo platform is optimized to fit up to four standard 60×40 cm Euroboxes, providing a practical and familiar loading space.

The robot can be operated remotely using the Cropkit Remote system, offering full control via smartphone. Alternatively, for those who prefer not to use a mobile device, the Cargo module is fully compatible with the Cropkit Walk module, which connects easily through the standard interface on the base unit. This flexibility allows farmers to choose the most convenient control method for their workflow and environment.

Figure 111: Cropkit Cargo

Figure 112: Cropkit Cargo Detail

4.1.8. Cropkit IQ

CropKit IQ represents the physical brain of the robot. It integrates a sensor suite consisting of an RGB-D camera and a bioacoustic microphone. The data collected through these sensors is processed and made accessible to farmers via a digital backend, which can be accessed through a smartphone or laptop. To support different needs, various subscription-based backend services are available, allowing farmers to choose the level of functionality that best suits their operations.

Figure 113: Cropkit IQ

IQ Logbook
The IQ Logbook uses collected field data to provide farmers with a clear overview of the current biomass status and crop types present in their fields. This allows farmers to track how different crops are developing over time and supports better decision-making in planning and crop management. The system makes it easy to log and access key data points—such as plant growth stages or yield estimates—helping farmers compare current conditions with previous seasons. For example, a farmer can quickly check how high their yield was at the same time last year. Since most data is still collected manually, and harvested yield remains one of the most frequently recorded metrics (see Chapter 2.2.5.3. Status Quo - Data Practices and Decision Influence), the IQ Logbook provides a simple yet powerful tool to streamline data collection and support more informed farm management.

IQ Scout
IQ Scout turns the Cropkit agricultural robot into a digital field investigator. Rather than relying on labour-intensive manual crop inspections, Cropkit Scout consistently evaluates plant health and identifies early indications of pest infestations with great accuracy. This empowers farmers to respond more quickly and strategically, addressing only the impacted areas and conserving time, resources, and crop protection products. By translating sensor data into specific action recommendations, autonomous scouting aids in protecting yields while minimising environmental harm.

When IQ Scout identifies something unusual, it promptly alerts the farmer, either through an app or a direct message, indicating the precise location (see Figure 114). The robot does not operate independently; instead, it functions as a decision-support tool, enabling the farmer to make informed choices. Following an on-site evaluation, the farmer can give feedback to the system: Was it genuinely a disease, or simply a false alarm? For instance, IQ Scout may flag a possible powdery mildew infection. Upon further examination, it may actually be harmless trichomes—plant hairs that have a similar appearance. The farmer rectifies the diagnosis directly in the app. This feedback is reintroduced into the system, allowing the robot to learn from it. Through a blend of auto-labelling and manual labelling, a smart learning process ensues. This "human-in-the-loop" methodology guarantees that IQ Scout becomes increasingly precise with every scouting mission, leading to ongoing improvement over time.

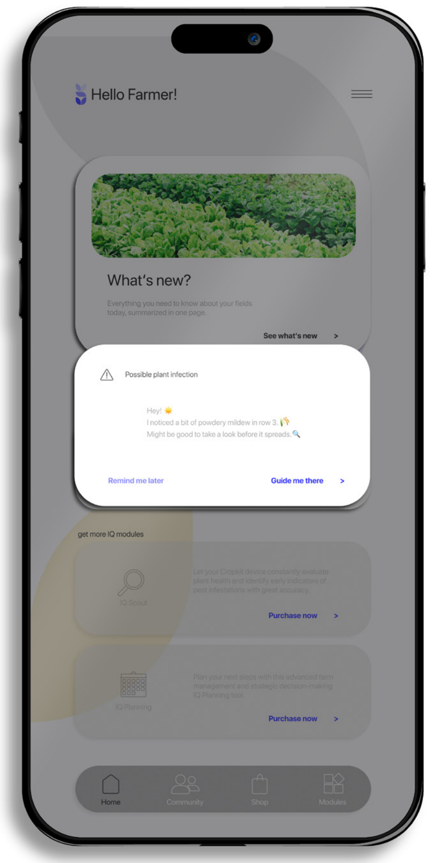


Figure 114: Cropkit IQ App Design - Allert

IQ Planning

IQ Planning is designed for advanced farm management and strategic decision-making. As part of the IQ suite, it integrates data from the IQ Logbook and IQ Scout, along with real-time weather information, to enable more accurate and forward-looking planning. This data-driven approach allows for advanced yield forecasting, which is especially valuable for farmers who rely on direct marketing. Over time, the system's deep learning models begin to identify patterns and correlations across seasons and crops, offering actionable insights based on long-term trends.

For example, it might detect that lettuce yields are consistently lower when sown in April and therefore suggest sowing in May instead. Since developments in the field are often influenced by a complex interplay of many variables, IQ Planning helps uncover these hidden relationships and supports better decision-making. However, it is not intended as a rigid decision-support tool. Rather, it acts as a discussion-support tool—presenting clear, data-backed insights that spark dialogue and guide collaborative, data-driven cropping strategies.

IQ Habitat

IQ Habitat takes a unique approach to ecological monitoring by literally "listening" to the land. The system utilises a bioacoustic microphone built into the IQ module to capture the farm's soundscape, enabling real-time biodiversity monitoring. Leveraging AI, it identifies species based on their vocalizations and detects insect activity by analyzing wingbeat frequencies and buzzing patterns. This approach, outlined in Chapter 2.3.1.5. The Role of Bioindicators in Informed Decision-Making, is part of an expanding field where sound serves as a glimpse into ecosystem health.

Bioacoustics is rapidly becoming a practical and effective method for monitoring environments in agricultural areas. By capturing and analyzing natural ambient sounds, it provides valuable information on species presence, distribution, behavior, and even their physiological state. For farmers, this offers a novel approach to assess and showcase the ecological results of their management practices—non-invasively, continuously, and in real-time (FAS, 2024).

Farmland soundscapes are filled with biological signals, particularly from birds and insects, which act as important indicators of environmental quality. For instance, the songs of birds found in fields or hedgerows often suggest a robust insect population and a varied habitat structure. Since their calls alter in response to environmental changes, birds are increasingly utilised as proxies for wider biodiversity. Shifts in bird song patterns can subtly but powerfully indicate changes in land use (Molina-Mora et al., 2024).

Insects play a vital role in acoustic monitoring. Machine learning algorithms can identify different species by analysing their flight tones or distinct sound-producing behaviours, including stridulation. The acoustic signatures of pollinators, such as bees and hoverflies, or pests like weevils and grasshoppers, provide insights into crucial ecological dynamics. A lively nighttime chorus of crickets or grasshoppers often indicates a healthy, minimally disturbed ecosystem. When placed near agricultural areas, acoustic sensors monitor pollinator activity, yielding valuable data on their abundance and diversity (Alberti et al., 2023). Soniferous insects, including cicadas, grasshoppers, and crickets, are particularly effective for evaluating habitat quality in mixed-use landscapes (Bennett et al., 2025). In addition to biodiversity monitoring, bioacoustics allows for the early detection of pest activity. Sounds such as locusts stridulating can act as early indicators of potential infestations, providing farmers the opportunity to intervene before damage escalates (Kohlberg et al., 2024).

Bioacoustics plays a crucial role in identifying broader environmental patterns. A decline in early morning birdsong or evening insect sounds may signal habitat degradation or the effects of agrochemicals. Conversely, a more diverse and vibrant soundscape often indicates ecological restoration, achieved through techniques such as hedgerow planting, cover cropping, and pond revitalisation. By consistently analysing soundscapes, farmers can observe the impact of their practices and adjust their approaches based on real-time feedback. As land use shifts—whether by eliminating natural features or adopting wildlife-friendly strategies—these changes manifest in the acoustic environment. This information offers an early, non-invasive insight into environmental trends, enabling proactive land stewardship. Field studies and pilot initiatives (AgriSound, 2024; FAS, 2024; Molina-Mora et al., 2024) have shown that acoustic monitoring is not only precise but also scalable, making it a valuable tool for contemporary, ecologically conscious agriculture.

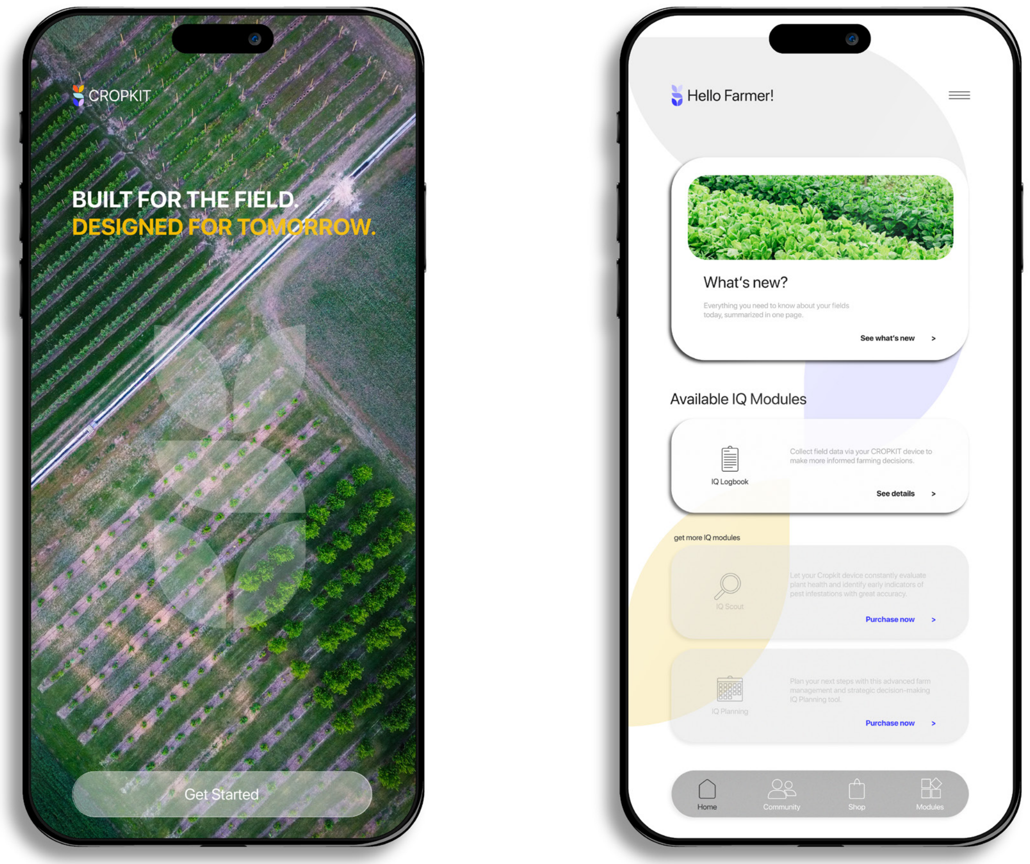


Figure 115: Cropkit IQ App Design - Selection of Digital Modules

IQ Edu

IQ Edu is tailored for farmers who are either new to agriculture or actively exploring new approaches, such as regenerative farming, low-input systems, or biodiversity-focused practices. While the other IQ backends provide data insights and visualizations, IQ Edu adds a dedicated learning layer. It interprets the data and explains what it means, why it matters, and how to act on it in more detail.

This includes guided tutorials, contextual tooltips, field examples, and beginner-friendly visualizations that break down complex agronomic or ecological relationships. For instance, when IQ Scout flags a disease, IQ Edu might explain the typical life cycle of the pathogen, potential environmental triggers, and sustainable treatment options—turning an alert into a teachable moment.

Unlike other modules that are mainly for experienced users, IQ Edu deliberately leans into explanation. The goal isn't just to support decisions, but to train the farmer's observational and interpretive skills over time. Research shows that seasonality slows learning in agriculture, and a lack of confidence or technical know-how can discourage new entrants (see Chapter 2.1.3.2. Main Challenges of Small-Scale Farms). IQ Edu addresses this by serving as a patient, on-demand mentor, lowering the barrier to entry and helping users gradually develop both theoretical understanding and practical intuition.

Figure 116: Exploaded View of the Lever Mechanism

4.2. Embodiment Evaluation

4.2.1. Materials Selection

Metallic Parts
Most metallic components are crafted from 7075 aluminium, selected for its remarkable strength-to-weight ratio, outstanding corrosion resistance, and reliable performance under challenging conditions. This high-performance alloy, mainly made up of aluminium, zinc, magnesium, and copper, is extensively utilised in the aerospace sector due to its exceptional mechanical characteristics. It provides tensile strength comparable to certain steels while being considerably lighter, making it ideal for applications that require both strength and reduced weight.

In agricultural settings, 7075 aluminium sustains its structural integrity under mechanical stress and resists damage from moisture, fertilisers, and severe weather, making it a dependable, low-maintenance option. For the initial low-volume production phase utilising CNC machining, 7075 was chosen for its superior machinability. However, as production increases and shifts to casting-based manufacturing, considering an alternative like A356-T6—better suited for casting—should be considered.

A mixed-material approach, using stainless steel for high-stress components and aluminium for other parts, was explored but ultimately rejected due to concerns about galvanic corrosion. This type of corrosion occurs when different metals come into electrical contact within an electrolyte, like salt or fertiliser-laden water, which can accelerate the degradation of the more anodic metal- in this case, aluminium. Additionally, the differing thermal expansion rates of stainless steel and aluminium could induce mechanical stress, threatening the integrity of the joints over time. As a result, the decision was made to adopt a full-aluminium structural design to ensure durability, thermal stability, and ease of manufacturing.

Plastic Components
Alongside the aluminium structural elements, high-density polyethylene (HDPE) was chosen for the assembly's plastic components because of its durability, UV resistance, and environmentally friendly properties. HDPE excels in outdoor agricultural environments, as it withstands degradation from extended sun exposure, moisture, fertilizers, and mechanical stress. It is resistant to cracking, corrosion, and deformation, ensuring dependable performance over long durations. From a sustainability standpoint, HDPE is fully recyclable and has a reduced environmental footprint compared to many other widely used plastics, thus meeting responsible sourcing and end-of-life recycling goals. Its blend of strength, weather resistance, and ecological benefits makes HDPE an excellent option for plastic parts in agricultural systems.

Float Module Cushions
The float module's prone bed surfaces feature TPU-laminated foam cushions that provide a perfect blend of comfort, durability, and environmental resilience. With an ergonomic foam core, they reduce physical strain during prolonged use. The thermoplastic polyurethane (TPU) outer layer offers excellent waterproofing and UV protection, ensuring dependable performance even in demanding field conditions. In contrast to conventional materials, TPU-coated foam withstands high-pressure cleaning without degrading, which is vital for keeping agricultural settings hygienic. Additionally, TPU serves as a more sustainable choice compared to PVC, often manufactured through low-VOC processes and containing recyclable materials. Thus, TPU-laminated cushions present a practical, durable, and eco-friendly option for the prone bed of the float module.

4.2.2.Manufacturing and Pricing

To establish a foundational understanding of Cropkit's pricing strategy, a preliminary cost estimation was performed. Each module was broken down into its primary components, with cost estimates assigned accordingly to build a baseline for production expenses. A profit margin is then applied to ensure both commercial viability and sustained investment in research and development.

Initially, a production run of 100 to 500 units is planned. During this phase, the first rollout of Cropkit modules will undergo continuous refinement through practical feedback gained from field trials, allowing for iterative enhancements to its mechanical and functional subsystems. The first units will utilise CNC machining, which enables quick changes and adjustments without the financial and temporal constraints commonly associated with moulding methods.
This low-volume production strategy avoids the substantial initial costs linked to injection or die-casting tooling. Once the design is stable and proven in the field, production can shift to injection moulding or die casting to upscale production and reduce unit costs.

The base module has a 100% profit margin. This covers the complexity of the product, the small production scale, and the need to fund further development, testing, and infrastructure. The goal is not to offer the cheapest product, but one that performs reliably in tough agricultural conditions and provides long-term value. For all additional modules beyond the base platform, a reduced profit margin of 20% is applied. This structure ensures that the base platform generates the primary revenue stream needed to fund continued R&D, while expansion modules remain economically accessible. This approach reflects a reverse razor-and-blades pricing model. The base unit offers substantial standalone value, while optional add-ons remain within reach, minimizing adoption barriers for farmers. All final prices include 21% VAT, as required in the Netherlands.

Cost Estimation Methodology

The table below outlines an estimated breakdown of component prices. Cost estimates for pre-fabricated parts are based on market research, while for custom-manufactured components, such as the aluminum frame, figures come from the CAD model that provides volume estimates. These volumes were modified to account for machining allowance and then multiplied by the corresponding material and processing rates. For instance, the Cropkit base frame will be CNC-machined from 7075-T6 aluminum. The CAD model estimates a raw material volume of about 9,000 cubic centimeters, or approximately 25 kilograms. With a 40% machining allowance, the total aluminum stock needed per unit rises to roughly 35 kilograms. Based on an estimated cost of €25 per kilogram, the material cost for each frame is around €890. CNC machining is projected to last three to four hours per unit, costing €80–100 per hour, leading to an extra €250–300 in machining expenses. An optional anodizing process, which improves corrosion resistance, adds around €30 per unit.

The following table provides a preliminary overview of all estimated costs.

	Cost Breakdown (until production) [€]	Profit & RD Margin [%]	Net Sales Price (Excl. VAT) [€]	VAT (21%) [€]	Approximate Final Retail Price (incl. VAT, rounded in €50 steps) [€]
Base					
Frame material (7075-T6 Al, 35.46 kg @ 25 €/kg)	890				
CNC machining (3–4 h @ 80–100 €/h)	300				
Anodizing finish	30				
2× 24 V linear actuators	300				
2× gas springs	60				
2× direct-drive hub motors	2.200				
2× rear pneumatic tires	120				
2× front swivel casters	100				
2× sealed 24 V Li-ion batteries	500				
Battery Management System	120				
Wiring, connectors & hardware	100				
Assembly (8–10 h @ 30 €/h)	250				
Total Production Cost	4.970	100	9.940	12.027	12.000
Walk					
Frame material (7075-T6 Al)	40				
CNC machining (0.5 h @ 80–100 €/h)	40				
Anodizing finish	5				
2× IP66 stop switches	20				
Wiring, connectors & hardware	20				
Assembly (0.5 h @ 30 €/h)	15				
Total Production Cost	140	20	168	203	200
Pilot					
RTK-capable GNSS antenna & receiver	300				
Stereo depth camera	120				
Mounting hardware & weather protection	20				
Wiring, connectors & cabling	15				
Assembly (0.5 h @ 30 €/h)	15				
Total Production Cost	470	20	564	682	700
Float					
Aluminum tube frame (30 mm × 3 mm)	60				
EVA foam padding	80				
Mounting brackets & hardware	25				
Assembly (0.75 h @ 30 €/h)	20				
Total Production Cost	185	20	222	269	250
Power					
24 V BLDC motor (3–5 kW)	600				
Motor controller	200				
Pulley/chain reduction system	60				
Housing, mounts, brackets & weather-sealing	40				
Electrical integration & cabling	20				
Assembly & testing (1 h @ 30 €/h)	30				
Total Production Cost	950	20	1.140	1.379	1.400
Cargo					
Steel/Aluminum platform (cut, welded, corrosion-resistant)	50				
Mounting brackets & hardware	20				
Assembly (0.5 h @ 30 €/h)	15				
Total Production Cost	85	20	102	123	150
IQ					
RGB-D camera	120				
Directional bioacoustic microphone	70				
AI edge computing unit	80				
Wireless module (Wi-Fi/Bluetooth)	20				
Mounting, housing & cabling	10				
Assembly (0.5 h @ 30 €/h)	10				
Total Production Cost	310	20	372	450	450

4.3. Market Strategy

4.3.1. Business Model

4.3.1.1. The Modules

Physical Modules

At the heart of the Cropkit ecosystem is the Cropkit Base, which serves as both the physical and economic foundation. Every user begins with full ownership of the Base unit, ensuring long-term security and freedom from vendor lock-ins. This ownership includes the Cropkit Walk module, providing an always-available manual control interface. From this starting point, users can tailor the ecosystem to their needs by selectively acquiring other modules either through direct purchase or flexible subscriptions.

This hybrid model allows farmers to grow into the system incrementally. A user might begin with only the Walk and Remote modules, and later add Pilot for autonomy, Cargo for logistics, or Float for ergonomic manual work—depending on their changing requirements and financial possibilities. The system does not require upfront investment in a complex, full-featured solution. Instead, it promotes organic growth aligned with each farm's scale, capability, and learning curve. The optional switch from subscription to ownership lowers total cost over time for modules that prove consistently useful, while the subscription-first approach encourages experimentation and reduces investment risks. This is particularly valuable in agriculture, where uncertainty—seasonal, financial, and climatic—is a constant factor.

Digital Modules

Where hardware modularity allows physical expansion, Cropkit IQ provides a modular digital extension of the ecosystem. The IQ suite—comprising Logbook, Scout, Planning, Habitat, and Edu—are offered via monthly or annual subscription plans, with users able to opt in or out depending on seasonal needs, budget, or priorities. More importantly, the modular structure of the IQ Suite mirrors that of the physical platform. A small-scale farmer might start with IQ Logbook, and later activate IQ Scout or Planning as their farm becomes more data-driven. Critically, IQ services run via the farmer's smartphone or laptop. There is no costly digital interface embedded into the robot—this design decision is both a technical and economic strategy. It reduces the complexity and fragility of hardware while leveraging devices the farmer already owns.

Unlike many contemporary ag-tech platforms, Cropkit empowers farmers by granting them full ownership of their collected data while also offering the option to share it voluntarily. Farmers who choose to share their anonymized data receive subscription discounts in return, creating an incentive that fuels a positive feedback loop. As more data is shared, machine learning models and insights improve, which leads to better outcomes for all users and encourages further participation. Data sharing remains entirely optional, reflecting an ethical commitment to agency and consent. This approach aligns with Cropkit's decentralized philosophy, ensuring that the platform never profits from farmers' data without their explicit permission and instead builds collective knowledge through transparency and trust.

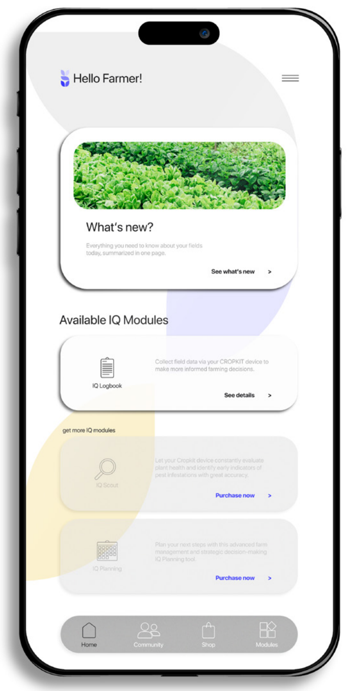


Figure 117: App Design with Community Button

4.3.1.2.Cropkit Community

A key aspect of the Cropkit business model is its strong focus on community. Farmers utilising Cropkit are not merely end users; they act as co-owners and collaborators within an expanding ecosystem. Each module features a standardized mechanical interface, facilitating the lending, leasing, or co-investing in equipment among farmers. This significantly decreases unnecessary purchases and promotes local collaboration, thereby supporting a decentralized equipment-sharing system that sharply contrasts with traditional top-down leasing or service models. For instance, neighboring farmers might collaboratively use a Pilot module for seasonal autonomous tasks or share a cargo platform during the harvest.

Cropkit also adheres to the principles of open hardware and innovation. It encourages farmers and makers to create tools specifically designed for their crops or environments and to share their experiences within the Cropkit community. A crucial component of this initiative is the "blank" interface, a modular attachment point that allows users to invent and construct their own implements for the Cropkit base unit. Many farmers are practical problem-solvers who relish the opportunity to craft their own solutions. With the blank interface, they can personalise their systems and even develop their toolsets beyond the offerings of the core product line. Consequently, Cropkit benefits from these grassroots innovations, gaining insights into additional modules or features that could serve the wider community.

Essentially, Cropkit transcends being just a product line; it acts as a dynamic, open, and collaborative platform that encourages farmers to influence the future of agriculture. It represents a movement characterised by shared value creation, the free exchange of knowledge, and empowering those closest to the land with the tools and autonomy to drive innovation.

4.3.1.3.Service and Maintenance

Cropkit's maintenance and service model is built on a network of authorized local dealers, blending the reliability of traditional service infrastructure with the adaptability of its modular design. Similar to established brands like John Deere and Fendt, Cropkit dealers provide a comprehensive range of support services, including routine maintenance, diagnostics, repairs, and access to original parts. Service packages are available in tiered plans, giving farmers flexibility—from basic preventive maintenance to full coverage with extended warranties and on-site support. Regional dealers stock and distribute parts and modules to ensure timely access when needed.

A key advantage of Cropkit's modular structure is the simplicity and speed of repairs, especially during time-sensitive periods such as harvest season. If a component fails, it can be quickly swapped out without causing major delays. The system is intentionally designed for ease of repair, with no glued parts and all components assembled using visible screws. This transparent, repair-friendly approach avoids the "black box" problem, making it far easier for farmers to carry out fast, independent repairs when necessary. For those who prefer hands-on maintenance, Cropkit offers detailed technical documentation and supports peer learning through its community platform, while certified repairs and upgrades remain available through the dealer network.

4.3.2. Branding

The name "Cropkit" clearly conveys its value proposition. The word "crop" emphasizes that the product is designed specifically for crop farming rather than livestock farming, reinforcing its connection to harvesting. The word "kit" suggests a complete, modular system—an ecosystem of tools working together. Both components of the name are monosyllabic and follow a consonant–vowel–consonant structure, making the name sound balanced, compact, and easy to remember.

The subclaim "Built for the field. Designed for tomorrow." was chosen because it succinctly captures the essence of the Cropkit ecosystem. "Built for the field" highlights the platform's durability, functionality, and real-world readiness—underscoring that Cropkit is a practical tool designed for everyday agricultural use, not just a concept from the lab. "Designed for tomorrow" reflects its future-oriented nature: modular, scalable, and built to support autonomous and data-driven farming. This tagline strikes a balance between present-day reliability and forward-looking innovation, making it compelling both for current users and future adopters. Its clarity, rhythm, and dual-focus make it an ideal expression of Cropkit's value in a single, memorable line.

The Cropkit logo visually captures the brand's essence by seamlessly merging nature and technology through a stylized fusion of a grain symbol with the letter's "C" (for Crop) and "K" (for Kit). Its clean, modular geometry reflects the system's scalable architecture—where physical and digital components fit together effortlessly. Soft, leaf-like curves evoke sustainability and natural growth, while the underlying grid-based structure communicates precision and engineering reliability. Together, these elements align with Cropkit's mission to provide durable, future-ready solutions for modern agriculture. The vertical, seed-inspired form symbolizes both deep roots in the field and upward-looking innovation—perfectly embodying the tagline: Built for the field. Designed for tomorrow.

The logo meets all key functional criteria for effective branding. It is fully scalable, ensuring clarity and sharpness at any size. For smaller applications, the wordmark can be reduced to just the symbol without losing recognizability. The design remains impactful in both colour and black-and-white formats, avoiding dependence on gradients or visual effects to maintain its identity.

Figure 118: Cropkit Logo Design

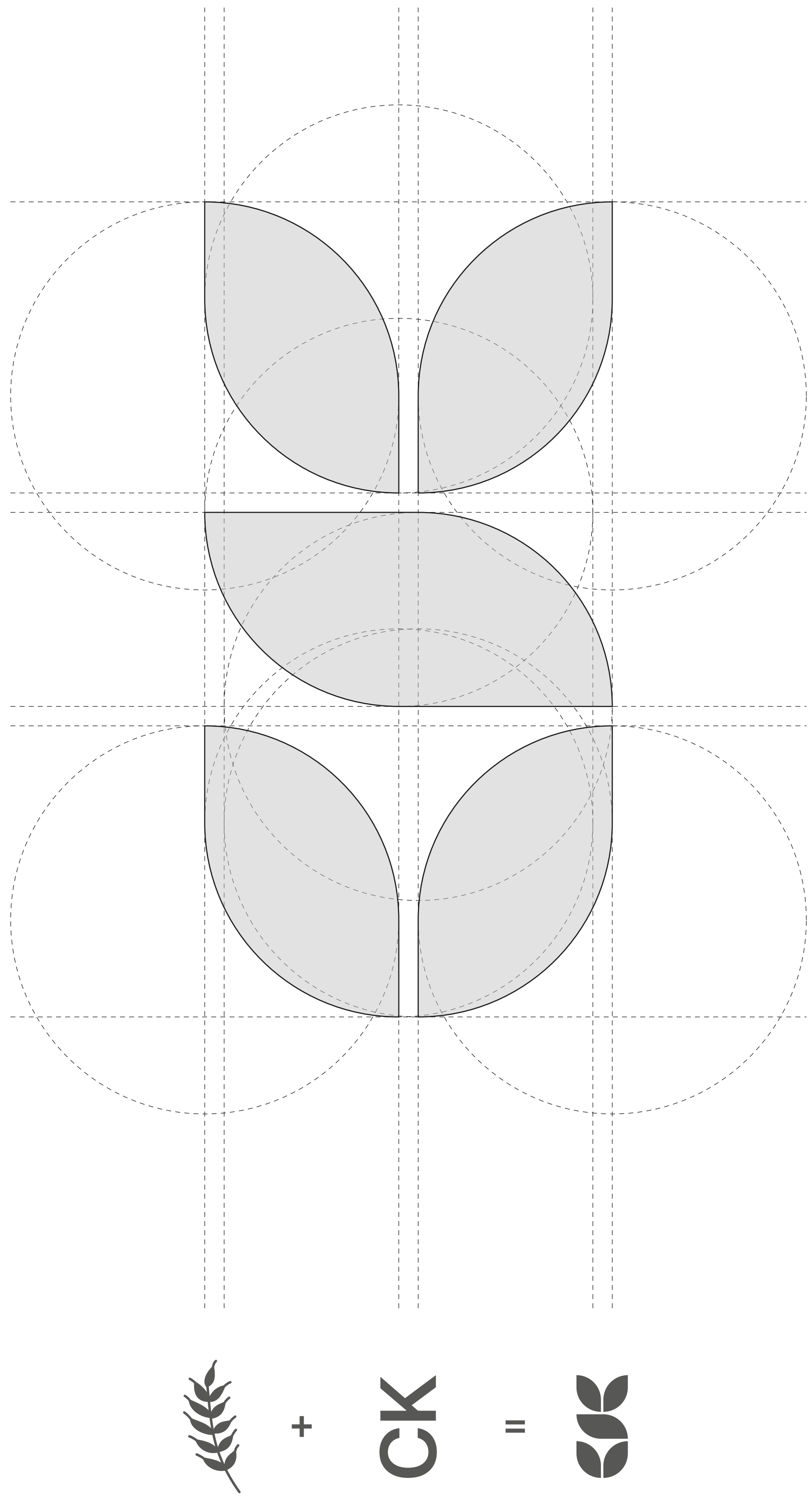


Figure 119: Cropkit Logo Meaning

Chapter 5

Discussion

5.1. Conclusion

The aim of this thesis was to support and enable the gradual adoption of precision agriculture technologies (PATs) for smallholder farmers. While the initial focus lay on implementing technology for its own sake, the course of the research revealed a more nuanced picture, highlighting both the real benefits and the potential drawbacks of PATs. It became increasingly clear that the value of these tools lies not in the technology itself, but in how it is designed and integrated into the lives and workflows of those who use it.

This work has illustrated the complex, interconnected challenges smallholders face. Through the concept of the vicious cycle, it has become evident where PATs must be strategically deployed in order to truly make a difference. The erosion of small farms is not just a symptom but a driver of deeper structural disruptions: monocultures, regulatory capture, environmental degradation, and the loss of rural identities. These forces feed back into the system, compounding the struggles of smallholders and accelerating their disappearance. As small farms vanish, the agricultural landscape becomes more homogenous, less resilient, and more vulnerable.

Today, PATs are too often applied at the wrong leverage points in this cycle. Agriculture doesn't just need incremental improvements through technology—it needs systemic, radical transformation. What we need is a diverse network of small, autonomous, resilient, and locally rooted farms—farms that cultivate a broad range of crops, enrich their ecosystems, and bolster local economies. To build this, we must fundamentally redirect innovation.

There is great potential in technology—but only if we abandon the techno-solutionist mindset that has failed us. Replacing dependency on subsidies with dependency on complex tools and opaque algorithms is not progress; it is repetition under a different name. True innovation means designing systems that are empowering by default: technologies that are affordable, adaptable, and free from hidden costs or constraints.

Cropkit represents a first step in this direction. It is the beginning of an open product ecosystem designed to make the farmer's life easier—modular, customisable, and interoperable. Its low entry barrier, modelled after a familiar tool—the two-wheel tractor—allows gradual, needs-based expansion through additional modules. This adaptability helps reduce dependency while respecting the farmer's autonomy and context.

This progress was only possible through close collaboration with farmers and ongoing engagement with stakeholders. It is essential to co-create with those most affected by these transformations. This research also made one thing clear: technology cannot solve all problems. We cannot simply throw innovation at a sector and hope for systemic change. We must understand the people behind the systems, their challenges, and their needs. Only then can we foster real innovation.

And this shift must happen quickly. Time is running out for agriculture. We need tools designed to support sustainable, resilient, and regenerative farming. Cropkit is intended to be one such tool, driving forward the urgently needed transformation of our agricultural systems.

5.2. Limitations and Recommendations

This thesis, while aiming to explore and propose meaningful solutions for small-scale farming through modular precision agriculture technologies, is subject to several limitations that should be acknowledged. These constraints also provide guidance for future research and development directions.

Temporal Scope
The most significant limitation of this work is its temporal scope: it was conducted within the time frame of a single academic semester. Agriculture, particularly in relation to emerging technologies, is a vast and complex field. Developing truly impactful solutions requires an in-depth understanding of the broader context—technological, ecological, and socio-political. While a comprehensive and interdisciplinary research approach was used to build contextual awareness, the scale and depth necessary for exhaustive exploration remained limited by time.

Market Research
While this thesis touches on available technologies in the agricultural sector, it lacks a detailed and systematic market analysis. A broader market study, identifying the full spectrum of existing Precision Agriculture Technologies (PATs) and their adoption levels, would be a valuable addition. Future projects should conduct in-depth benchmarking of commercial solutions to understand adoption barriers and opportunities more clearly.

Quantitative Data Limitations
The online survey conducted included responses from 44 participants across the Netherlands, Germany, and Austria. Although the analysis indicated that nationality did not significantly affect response patterns, the sample size remains too small for generalizable conclusions. Additionally, some responses were included from farms exceeding 10 hectares, which may have introduced variability not representative of small-scale farming. Future studies should aim for larger, more structured, and regionally stratified samples.

Physical Prototyping and Testing
The embodiment of the Cropkit system remains conceptual and digital in nature. Particularly in the "Float" configuration, which places high mechanical demands on the system due to rough terrain, thorough real-world testing is critical. Future work should include extensive prototyping and field trials to assess durability, mobility, and operational reliability under real farming conditions.

Digital Backend and Sensor Integration
Another important limitation lies in the underdeveloped state of the digital backend. Even the most advanced sensors are ineffective without reliable data processing, interpretation, and decision support. In this thesis, the digital components—including AI, computing power, and software integration—were only partially addressed due to scope constraints. Future iterations should focus more extensively on this aspect, particularly in refining the Trait-Sensor-Relation framework to include computing limitations.

Modular Design and Adaptability
The current Cropkit track width is fixed at 800 mm, based on standard bed widths in market gardening (typically ~750 mm). However, adaptability will be crucial for broader applicability. Future design improvements should explore adjustable wheel spacing, potentially using modular spacers at the front arm and rear brace to allow for flexible configurations.

Cabling and Control Interfaces
Cabling and wire management are not yet integrated into the design. This is a key technical gap that should be resolved to ensure system robustness and maintainability. Additionally, in the Cropkit Float configuration, user control is currently limited to a smartphone interface via Cropkit Remote. A more ergonomic, foot-operated control system—commonly found in prone weeders—could enhance usability and should be further developed.

User Interface – Cropkit Walk
The current Cropkit Walk setup includes controls only for left and right motors. It lacks an interface for operating linear actuators, which are necessary to raise and lower implements. A dedicated switch or control interface should be added in future iterations to enable full user functionality.

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Chapter 6

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Chapter 7

Appendices

7.Project Brief

TU Delft

IDE Master Graduation Project

Project team, procedural checks and Personal Project Brief

In this document the agreements made between student and supervisory team about the student's IDE Master Graduation Project are set out. This document may also include involvement of an external client, however does not cover any legal matters student and client (might) agree upon. Next to that, this document facilitates the required procedural checks:

- Student defines the team, what the student is going to do/deliver and how that will come about
- Chair of the supervisory team signs, to formally approve the project's setup / Project brief
- SSC E&SA (Shared Service Centre, Education & Student Affairs) report on the student's registration and study progress
- IDE's Board of Examiners confirms the proposed supervisory team on their eligibility, and whether the student is allowed to start the Graduation Project

STUDENT DATA & MASTER PROGRAMME

Complete all fields and indicate which master(s) you are in

Family name	Soche	IDE master(s)	IPD ✓ Dfl ☐ SPD ☐
Initials	D.S.	2nd non-IDE master	
Given name	David	Individual programme (date of approval)	
Student number	5901820	Medisign	☐
		HPM	☐

SUPERVISORY TEAM

Fill in he required information of supervisory team members. If applicable, company mentor is added as 2nd mentor

Chair	Jan Willhelm Hoftijzer	dept./section	HCD
mentor	Marco Rozendaal	dept./section	HCD
2nd mentor	Martin Steffner		
client:	NPK Design		
city:	Leiden	country:	Netherlands
optional comments	While Mr. Hoftijzer focuses on Design Visualization and has expertise in visualization (one of my personal learning goals), Mr. Rozendaal focuses on Human-Robot Interaction and has expertise in robotics (a valuable expertise essential for the project).		

! Ensure a heterogeneous team. In case you wish to include team members from the same section, explain why.

! Chair should request the IDE Board of Examiners for approval when a non-IDE mentor is proposed. Include CV and motivation letter.

! 2nd mentor only applies when a client is involved.

APPROVAL OF CHAIR on PROJECT PROPOSAL / PROJECT BRIEF -> to be filled in by the Chair of the supervisory team

Sign for approval (Chair)

Name [redacted] Date 22-11-2024 Signature [redacted]

CHECK ON STUDY PROGRESS

To be filled in **by SSC E&SA** (Shared Service Centre, Education & Student Affairs), after approval of the project brief by the chair. The study progress will be checked for a 2nd time just before the green light meeting.

Master electives no. of EC accumulated in total ______ EC

Of which, taking conditional requirements into account, can be part of the exam programme ______ EC

X	YES	all 1st year master courses passed
	NO	missing 1st year courses

Comments:

Sign for approval (SSC E&SA)

Name [redacted] Date 11-02-2025 Signature [redacted]

APPROVAL OF BOARD OF EXAMINERS IDE on SUPERVISORY TEAM -> to be checked and filled in by IDE's Board of Examiners

Does the composition of the Supervisory Team comply with regulations?

YES	V	Supervisory Team approved
NO		Supervisory Team not approved

Comments:

Based on study progress, students is ...

V	**ALLOWED** to start the graduation project
	NOT allowed to start the graduation project

Comments:

Sign for approval (BoEx)

Name [redacted] Date 11/2/2025 Signature [redacted]

Name student David Soche **Student number** 5,901,820

PROJECT TITLE, INTRODUCTION, PROBLEM DEFINITION and ASSIGNMENT
Complete all fields, keep information clear, specific and concise

Project title Facilitating Precision Farming Adoption in Smallholder Agriculture

Please state the title of your graduation project (above). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.

Introduction

Describe the context of your project here; What is the domain in which your project takes place? Who are the main stakeholders and what interests are at stake? Describe the opportunities (and limitations) in this domain to better serve the stakeholder interests. (max 250 words)

The project focuses on the agricultural sector, particularly the role of smallholder farmers (e.g., market gardens) in Europe (geographical focus shaped by research), who are critical to global food security (Azadi et al., 2022; Galli et al., 2020). Their success is essential for meeting the projected food demands of the growing global population by 2050 (Dhillon & Moncur, 2023).

Precision farming (PF) technologies, including environmental monitoring, crop and soil assessment, and the automation of field tasks, offer significant opportunities for smallholder farmers. These technologies deliver substantial ecological and economic benefits by enabling data-driven decision-making and automating various agricultural processes (Buitkamp et al., 2021; Cui et al., 2018; John et al., 2023).

Contrary to the belief that precision farming and automated systems predominantly benefit large agricultural enterprises, evidence indicates that the greatest efficiencies are realized on smaller plots: The smaller the field, the greater the benefits of autonomous machines in terms of field efficiency (Al-Amin et al., 2022; Dhillon & Moncur, 2023). However, smallholders often exhibit reluctance to adopt PF technologies (Al-Amin et al., 2022; Dhillon & Moncur, 2023; John et al., 2023; Lowenberg-DeBoer et al., 2019; Monteiro et al., 2021; Paustian & Theuvsen, 2016; Reichardt et al., 2009). This hesitance is concerning, particularly given the ongoing decline of small farms, driven by the prevailing attitude in agriculture - "get big or get out" (Al-Amin et al., 2022). More than two-thirds of farms in the European Union are smaller than five hectares. Between 2005 and 2020, the number of farms in the EU declined by 37%, with small farms accounting for 87% of this decrease (Eurostat, 2022). By adopting PF practices, small farms can enhance their viability and establish themselves as economically sustainable alternatives to large-scale agriculture, reducing their dependence on subsidies (Al-Amin et al., 2022).

However, it is crucial to integrate this technology into farming systems in a way that promotes environmental and social sustainability for smallholder farmers. The human-robot interaction (HRI) should be carefully considered to ensure that technology supports rather than disrupts natural ecosystems, fostering a sustainable balance between innovation and the environment.

→ space available for images / figures on next page

Personal Project Brief – IDE Master Graduation Project

Problem Definition

What problem do you want to solve in the context described in the introduction, and within the available time frame of 100 working days? (= Master Graduation Project of 30 EC). What opportunities do you see to create added value for the described stakeholders? Substantiate your choice.
(max 200 words)

Smallholders' reluctance to adopt precision farming (PF) technologies constrains their capacity to achieve substantial economic and ecological benefits (Paustian & Theuvsen, 2016). Key barriers to adoption include substantial initial investment costs, uncertainties about return on investment (ROI), and a perceived lack of benefits, all of which significantly hinder the implementation of PF practices (John et al., 2023; Paustian & Theuvsen, 2016).

Current agricultural robots are often application-specific and require substantial investment, leaving a gap for accessible and scalable solutions (Lowenberg-DeBoer et al., 2019). A modular agricultural robot system, with a scalable design, could bridge this gap by offering simple construction and adaptability for smaller operations (Guri et al., 2024). This system can support various implements for environmental monitoring, soil assessment, and automating tasks like tilling, seeding, and fertilisation.

A modular design reduces initial investment costs and allows for the gradual integration of PF technologies. Farmers can incrementally transition from manual to semi-autonomous and fully autonomous systems, akin to a tractor with interchangeable implements but with advanced automation capabilities. This approach fosters acceptance and innovation, enabling small-scale farmers to adopt new technologies, thereby facilitating a more sustainable and economically viable farming model.

Assignment

This is the most important part of the project brief because it will give a clear direction of what you are heading for. Formulate an assignment to yourself regarding what you expect to deliver as result at the end of your project. (1 sentence) As you graduate as an industrial design engineer, your assignment will start with a verb (Design/Investigate/Validate/Create), and you may use the green text format:

Design a product to facilitate the incremental integration of precision farming practices for smallholder farmers.

Then explain your project approach to carrying out your graduation project and what research and design methods you plan to use to generate your design solution (max 150 words)

The graduation project will adopt a structured, multi-phase approach. P1 focuses on research and analysis, emphasizing problem definition and user understanding through a literature review, qualitative interviews, and possibly a quantitative (online) survey. Context mapping and market analysis will support developing a clear problem statement, a list of requirements and a Product Breakdown Structure (PBS), supplemented by technology scouting to identify suitable technologies. P2 involves concept generation through ideation techniques and morphological charts, using evaluation methods such as the Harris Profile and `quick-and-dirty prototyping' to determine the most promising solutions. P3 refines the chosen concept with more advanced prototypes and CAD models, ensuring seamless system integration while detailing the final design, including technical specifications, aesthetics, material selection, and completed CAD models, with potential user testing. P4 focuses on constructing the final prototype, with the different Technology Readiness Levels (TRLs) for each item defined in the PBS in advance. Finally, P5 concludes the project with thorough documentation and presentations to communicate the outcomes effectively.

Project planning and key moments

*To make visible how you plan to spend your time, you must make a planning for the full project. You are advised to use a Gantt chart format to show the different phases of your project, deliverables you have in mind, meetings and in-between deadlines. Keep in mind that all activities should fit within the given run time of 100 working days. Your planning should include a **kick-off meeting**, **mid-term evaluation meeting**, **green light meeting** and **graduation ceremony**. Please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any (for instance because of holidays or parallel course activities).*

Make sure to attach the full plan to this project brief.
The four key moment dates must be filled in below

Kick off meeting 18 Nov 2024

Mid-term evaluation 10 Feb 2025

Green light meeting 14 Apr 2025

Graduation ceremony 26 Mai 2025

In exceptional cases (part of) the Graduation Project may need to be scheduled part-time. Indicate here if such applies to your project

Part of project scheduled part-time	
For how many project weeks	
Number of project days per week	

Comments:

Motivation and personal ambitions

Explain why you wish to start this project, what competencies you want to prove or develop (e.g. competencies acquired in your MSc programme, electives, extra-curricular activities or other).

Optionally, describe whether you have some personal learning ambitions which you explicitly want to address in this project, on top of the learning objectives of the Graduation Project itself. You might think of e.g. acquiring in depth knowledge on a specific subject, broadening your competencies or experimenting with a specific tool or methodology. Personal learning ambitions are limited to a maximum number of five.
(200 words max)

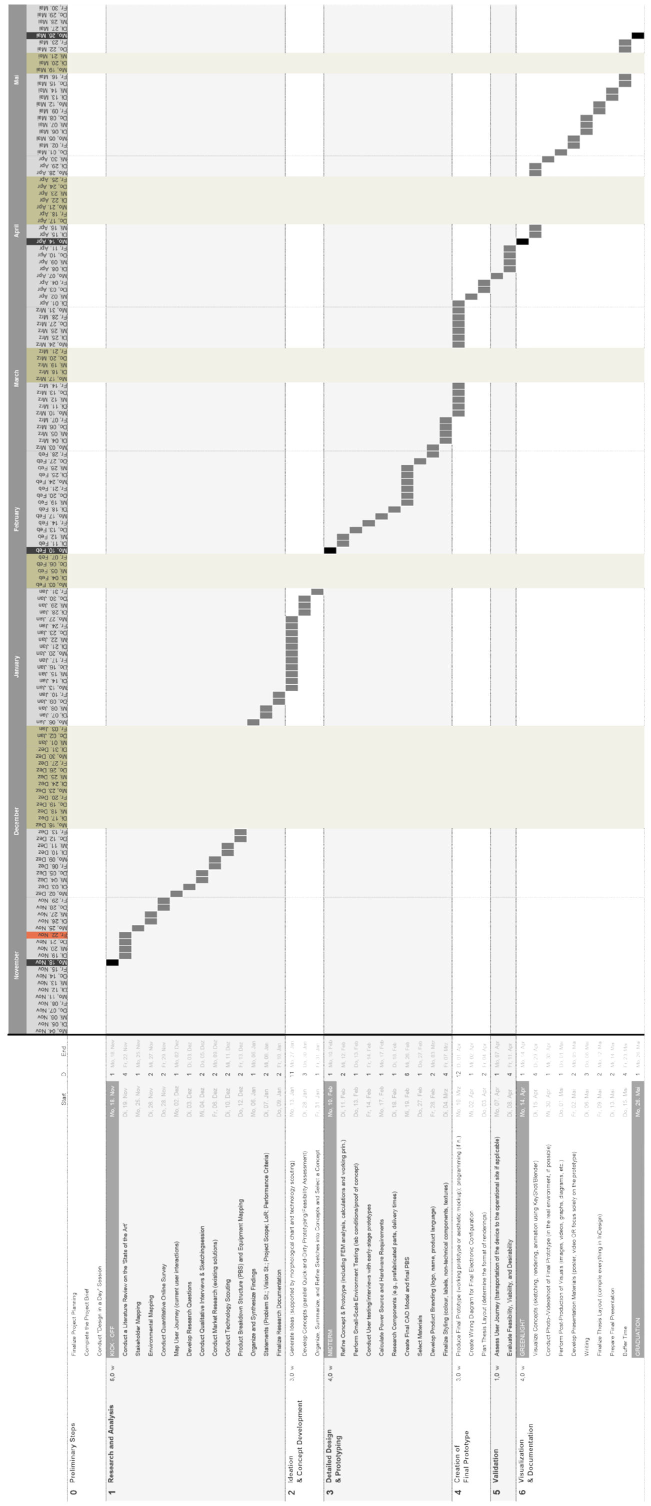
This project aims to refine and encompass several competency areas. One objective is to enhance my engineering skills through the development of a complex product that incorporates multiple layers of functionality, including moving parts and a comprehensive system architecture. This undertaking will not only deepen my understanding of fundamental mechanical principles but also advance my systems thinking abilities. The project further explores the aesthetics of transportation design, an area in which I possess limited prior experience. My objective is to broaden my expertise, enhance my portfolio, and increase my appeal to potential employers within this design domain. This initiative presents a valuable opportunity to deepen my technical knowledge, mechanical engineering skills, and capabilities in visualization and sketching. By integrating these competencies, I aim to create a harmonious synergy between technical feasibility and aesthetic design, all while addressing user needs. By synthesising these skills, I aspire to present a well-rounded skillset that seamlessly merges functionality with aesthetic appeal.

Rapid Prototyping with Electronics: My goal is to build confidence in the swift development of simple, functional prototypes utilising basic electronics and Arduino technology. I will focus on integrating components such as motors, printed circuit boards (PCBs), and batteries throughout the development process. This aspiration underscores my commitment to acquiring fundamental skills in electronics prototyping.

Enhancement of Sketching Abilities: I aim to refine my sketching skills specifically in the context of mobility concepts. My objective is to represent innovative and functional design ideas with greater clarity and precision, thereby improving my ability to visually communicate complex concepts effectively.

Deepening Mechanical Engineering Knowledge: I intend to enhance my understanding of mechanical engineering by utilising tools such as Finite Element Analysis (FEA). My objective is to acquire sufficient knowledge to evaluate and justify the feasibility of my design concepts.

PLANNING



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7.2. Terminology of Small-Scale Farms

Farm Sizes
Farm size, alongside Standard Output (SO), is a key classification factor. While often measured in hectares, it can also be assessed by economic size, labour force, livestock numbers, crop production or overall farm structure (Guiomar et al., 2018). In the EU, hectares remain the primary metric for analysing agricultural structures, mapping farm distribution, and understanding production patterns (Rossi & EPRS, 2022).

Hectare-based classification is widely used for its simplicity (Guiomar et al., 2018; Rossi & EPRS, 2022). Farms with less than five hectares are typically classified as small. However, this method can be misleading. A small landholding with intensive livestock production, such as a large pig shed, may still qualify as a large operation in terms of SO. Despite these limitations, land area remains the most accessible indicator, especially in regions with limited resources for detailed agricultural surveys (Rossi & EPRS, 2022).

Relying solely on a single criterion, such as farm size, limits the effectiveness of classification systems designed for broader agricultural assessments (Guiomar et al., 2018). Moreover, terms like 'small-scale farm', 'smallholder', 'small-scale farm' and 'family farm' lack universally accepted definitions. The scientific literature reflects considerable debate over these definitions, with various approaches proposed (Bartkowski et al., 2022; Davidova & Thomson, 2013; FAO, 2017; Guiomar et al., 2018; Nyambo et al., 2019). Although these terms are sometimes used interchangeably, their meanings can vary significantly depending on the agricultural context. Clarifying these definitions is crucial for understanding both their overlaps and their distinctions.

Smallholder and Small-Scale Farm
Definitions of 'smallholder' or 'small-scale farm' vary widely, incorporating factors such as farm size, production techniques or technologies, family labour involvement, and economic impact (FAO, 2017). Various studies have characterised smallholder farmers using different approaches (Nyambo et al., 2019). In practice, 'smallholder' often emphasises land tenure or usage, whereas 'small-scale farm' is more directly linked to production levels. Nonetheless, the Food and Agriculture Organisation (FAO) suggests that these terms can be used interchangeably because they describe very similar actors (FAO, 2017).

Small-Scale Farm
The term 'Small-Scale Farm' typically refers to the size of the farmland, although this definition has its limitations (Rossi & EPRS, 2022). Within the European Union, Eurostat defines small-scale farms as those with an agricultural area of less than five hectares (Davidova & Thomson, 2013; Eurostat, 2022; Guiomar et al., 2018). In contrast, the FAO characterises small-scale farms as those with less than ten hectares (FAO, 2013).

Family Farm
The terms 'small-scale farm' and 'family farm' are sometimes used interchangeably - a practice that can be misleading (Guarín et al., 2020; Lowder et al., 2016; Rossi & EPRS, 2022). There is no universally accepted definition for 'family farm'. Typically, the term refers to the management structure rather than the farm's size. Over 90% of farms worldwide are considered family farms, while the other terms often emphasise different criteria (Lowder et al., 2016). Although there is significant overlap between small-scale farms and family farms, not all family farms are small (Rossi & EPRS, 2022). According to Eurostat, a family farm is defined as one in which 50% or more of the agricultural labour force is provided by family members, independent of the farm's size (Eurostat, 2022).

7.3. Subsidies and Regulations

Agricultural structures are closely linked to subsidies and political measures. To examine how these policies influence farmland, particularly small-scale farms, the following section provides an overview. This is a crucial topic, as the survival of small-scale farms in Europe is significantly shaped by subsidies, though their impact varies depending on regional differences and farm types. Many survive primarily through financial subsidies rather than economic self-sufficiency (Al-Amin et al., 2022). The European Union's agricultural policies include specific measures aimed at supporting small-scale farms, yet most agricultural funds are allocated to larger farms (Rossi & EPRS, 2022). To get a better understanding of this, also an interview was conducted with an expert in agricultural policy and subsidy management.

7.3.1. Common Agricultural Policy (CAP)

The Common Agricultural Policy (CAP) is a set of laws adopted by the European Union (EU) to establish a unified agricultural policy across its Member States. Initially created in 1962 by the six founding countries of the European Communities, it remains the EU's oldest ongoing policy. The CAP is designed to support agriculture and rural development within the EU, with primary goals of promoting sustainable food production, enhancing rural economies, and contributing to environmental and climate objectives (Pe'er et al., 2019). It oversees and finances all agricultural support within the EU, making it a crucial instrument in advancing the European Green Deal. In its most recent revision, the CAP was significantly restructured to align more closely with the Green Deal's objectives (European Union, 2022b, 2023).

The CAP Strategic Plan Regulation 2023-2027

(CSP) is a fundamental component of the Common Agricultural Policy (CAP), providing the framework and strategic direction for its implementation across EU Member States. For the period 2023-2027, the CAP is built around ten key objectives, addressing social, environmental, and economic priorities. These objectives form the basis upon which each Member State has developed its CAP Strategic Plan (European Union, 2022a).

The CAP Strategic Plans (CSP) are financed through two key EU budget funds:

European Agricultural Guarantee Fund (EAGF) – Pillar 1:

- Fully financed by the EU.
- Provides direct payments to farmers.
- Supports market stability measures.

European Agricultural Fund for Rural Development (EAFRD) – Pillar 2:

- Co-financed by Member States.
- Supports rural development initiatives.
- Delivered through grants or financial instruments.

These funds operate under distinct programming approaches. EAGF support is provided annually, ensuring direct financial assistance, whereas EAFRD support follows a multi-annual structure, involving area-related payments and long-term commitments (European Union, 2023; Pe'er et al., 2019)The accompanying graph provides a visual representation of the subsidy distribution structure (see Figure 120).

Structure of

Subsidy Distribution.

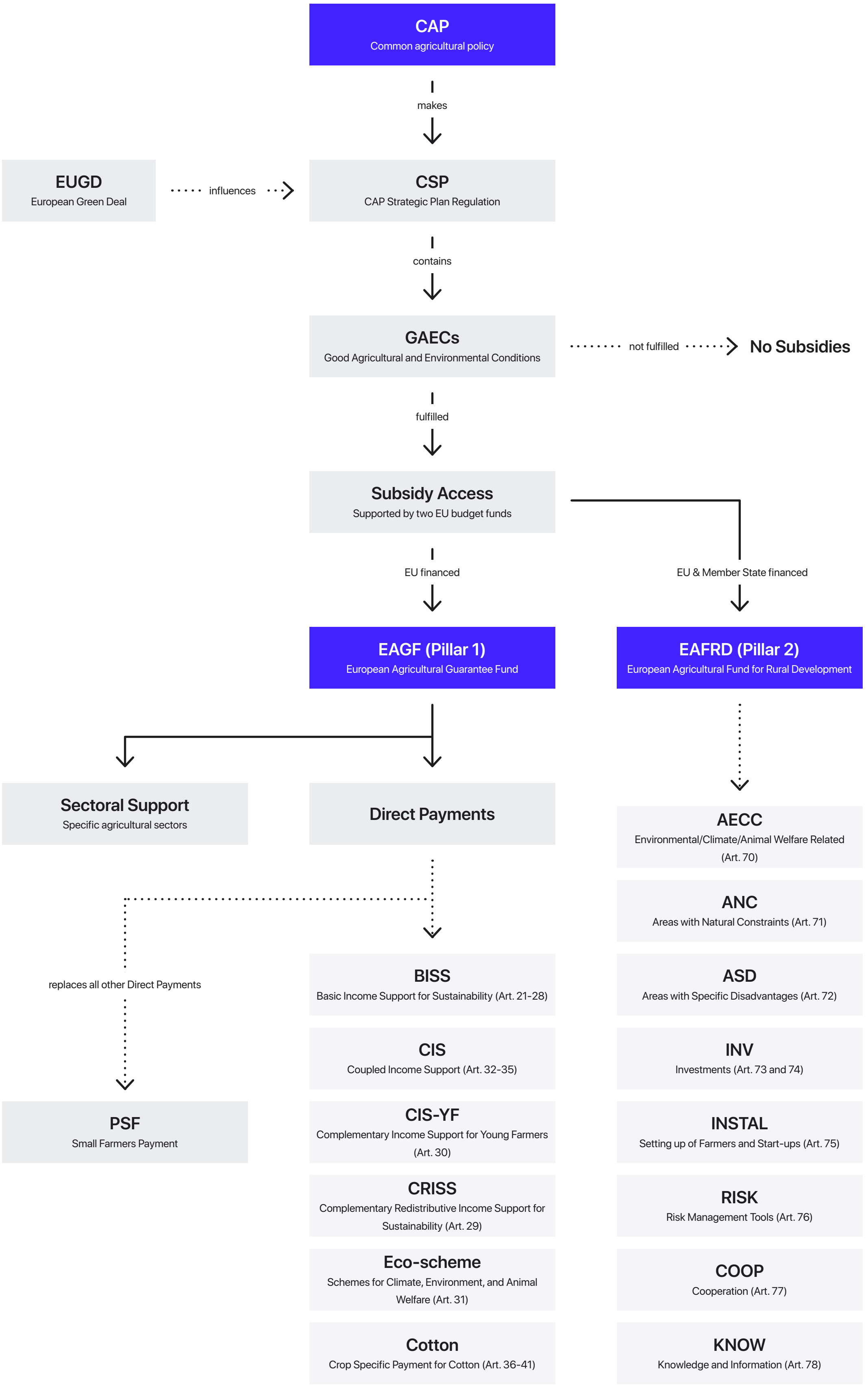


Figure 120: Structure of Subsidy Distribution. Created by author, based on (European Commission, 2023a; European Union, 2022b, 2022a, 2023)

The reformed CAP (2023-2027), with a total budget of €264 billion, represents a strategic shift towards sustainability-driven agriculture. The European Agricultural Guarantee Fund (EAGF), amounting to €198 billion, remains the primary vehicle for direct payments (€189.1 billion), including Basic Income Support (€96.7 billion) and Eco-Schemes (€44.7 billion), the latter aimed at climate action.

Simultaneously, the European Agricultural Fund for Rural Development (EAFRD), with €66 billion, plays a crucial role in strengthening rural development. Within this budget, €20.3 billion is allocated to environmental and animal welfare initiatives, while €18.4 billion is dedicated to investment programs.

This financial structure aligns the CAP with the EU Green Deal and the Farm to Fork Strategy, ensuring a more sustainable and resilient agricultural sector. The budget distribution is illustrated in Figure 121.

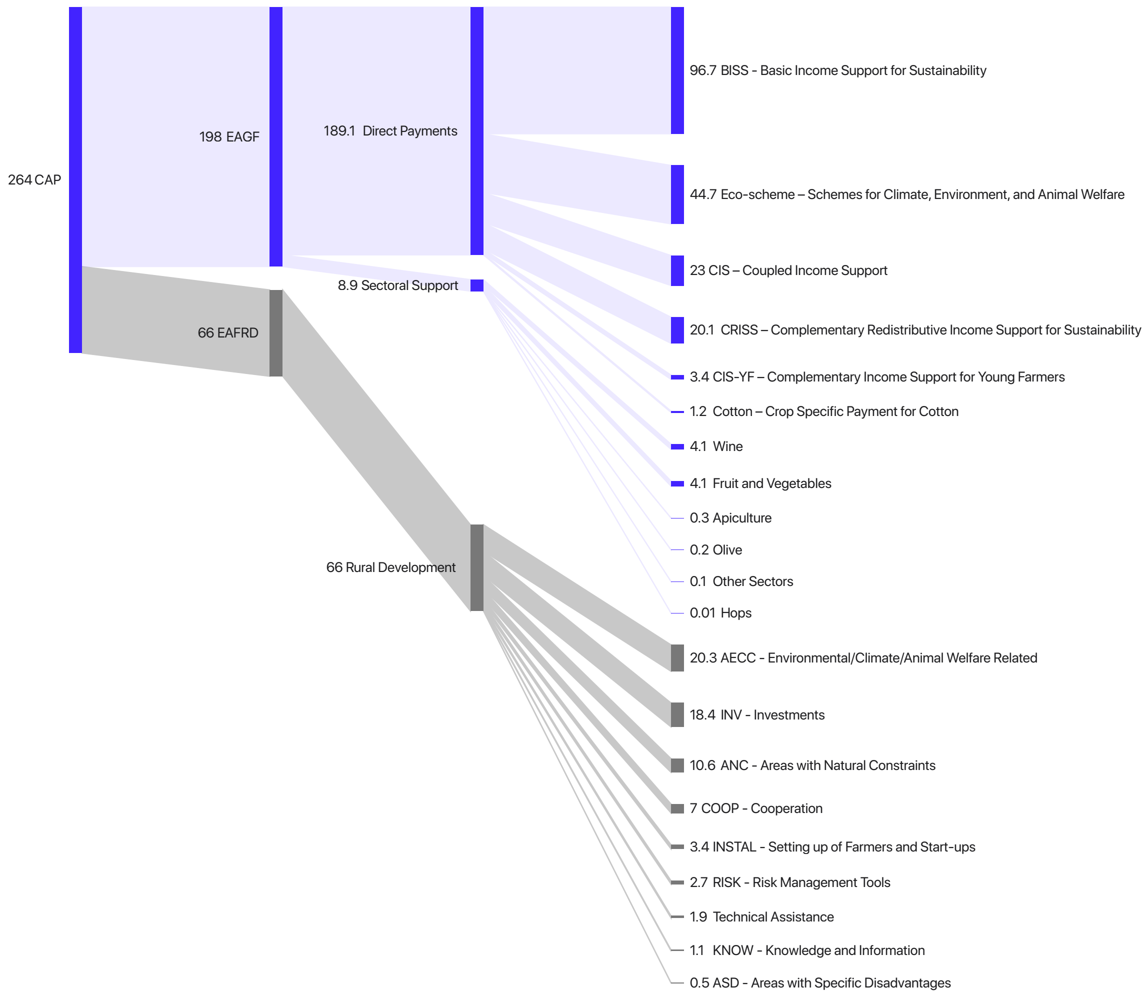


Figure 121: Distribution for EAGF and EAFRD (2023-2027). Created by author, based on (European Commission, 2023a; European Union, 2022b, 2022a, 2023)

Types of Subsidies Available under the CAP

BISS – Basic Income Support for Sustainability (Articles 21-28):
BISS offers a safety net for farmers by helping to close the gap between agricultural income and average wages. It is an area-based support scheme that provides a fixed amount per hectare each year. This is one of the key tools within the Common Agricultural Policy (CAP) to ensure income support for EU farmers. To qualify, farmers must meet the Good Agricultural and Environmental Conditions (GAECs) of their respective EU member states. In the EU, the average BISS payment per hectare is €134 (European Commission, 2023b).

CRISS – Complementary Redistributive Income Support for Sustainability (Article 29):
CRISS redistributes income support from larger to smaller and medium-sized farms by providing additional payments for the first hectares under BISS. As a key element of the 2023-2027 CAP, Member States must allocate at least 10% of their adjusted financial allocation for direct payments (after transfers between funds) to CRISS. This aims to ensure that smaller and medium-sized farms receive higher payments.

CIS-YF – Complementary Income Support for Young Farmers (Article 30):
CIS-YF provides financial support to help young farmers establish and sustain their agricultural businesses. It offers additional payments per hectare or a lump sum to young farmers who meet specific eligibility criteria.

CIS – Coupled Income Support (Articles 32-35):
CIS allows EU member states to offer targeted support to specific agricultural sectors or farming types. This support aims to stabilize incomes in volatile markets and is directly linked to the production of certain crops or livestock. Payments are based on the quantity or area of production for specific crops or animals.

Fruit and Vegetables (Articles 49-53):
Financial assistance for fruit and vegetable producers aimed at enhancing competitiveness and sustainability.

AECC – Environmental/Climate/Animal Welfare Related (Article 70):
AECC encourages practices that safeguard the environment, mitigate climate change, and promote animal welfare.

ANC – Areas with Natural Constraints (Article 71):
Support for farmers in regions with natural constraints, providing compensation for the environmental challenges they face.

ASD – Areas with Specific Disadvantages (Article 72):
Assistance for farmers in disadvantaged areas, supporting them in maintaining operations despite local challenges.

INV – Investments (Articles 73-74):
Support for investments in agricultural infrastructure, technology, and sustainable practices to enhance productivity and environmental performance.

INSTAL – Setting up of Farmers and Start-ups (Article 75):
Financial aid for new farmers and start-ups to establish and grow their farms.

RISK – Risk Management Tools (Article 76):
Support for risk management tools to help farmers manage price volatility, natural disasters, and market fluctuations.

COOP – Cooperation (Article 77):
Encourages collaboration among farmers to enhance productivity, sustainability, and innovation.

KNOW – Knowledge and Information (Article 78):
Provides access to knowledge, training, and information to improve farming practices and competitiveness.

Good Agricultural and Environmental Conditions (GAECs)
To qualify for funding under the Common Agricultural Policy (CAP), farmers must comply with the Good Agricultural and Environmental Conditions (GAECs). These standards serve as a prerequisite for full CAP support, addressing climate change, water management, soil health, biodiversity, and landscape conservation. The latest version includes nine specific thematic areas.

GAEC 1: Permanent grassland
GAEC 2: Protection of wetland and peatland
GAEC 3: Ban on burning arable stubble
GAEC 4: Buffer strips along water courses
GAEC 5: Tillage management
GAEC 6: Minimum soil cover
GAEC 7: Crop rotation
GAEC 8: Non-productive areas and features
GAEC 9: Ban on converting and ploughing permanent grasslands in Natura 2000 sites

Failure to meet GAEC requirements results in financial penalties or loss of support. Designed to reflect local and national conditions, GAECs apply to nearly 90% of agricultural land in the EU (European Commission, n.d.; European Union, 2022a, 2022b, 2023).

7.3.2. Subsidies for Sustainable Practices

Eco-schemes - Schemes for Climate, Environment, and Animal Welfare (Article 31) - are voluntary programs designed to incentivise farmers to adopt environmentally friendly agricultural practices, including climate action, biodiversity conservation, and improved animal welfare. As part of the Common Agricultural Policy (CAP), these schemes aim to support the implementation of sustainable land management practices. They can introduce new environmentally beneficial practices, expand existing ones, or both.

Member States have flexibility in tailoring these schemes to their national agricultural contexts, leading to the development of 158 unique eco-schemes across the EU. Of these, 18% provide 'top-up' payments in addition to the Basic Income Support for Sustainability (BISS), while 82% compensate farmers for additional costs and income losses. Eco-schemes that include 'top-up' payments typically focus on enhancing biodiversity, preserving non-productive landscape features, or adopting a 'whole-farm approach' (European Union, 2023). An analysis of the strategic plans of different Member States reveals that 'soil conservation practices' and 'landscape and biodiversity conservation' play a significant role in all national CAP Strategic Plans (CSPs).

A broader examination of thematic objectives across all 28 CSPs further confirms that 'soil conservation practices' and 'landscape and biodiversity conservation' remain central priorities in eco-schemes.

Each EU Member State has developed its own eco-schemes, offering financial support to farmers based on their environmental performance. In the Netherlands, for example, a points-based system within the CAP incentivises sustainable farming practices. Farmers can select from 22 eco-activities, including crop diversification, organic farming, and biodiversity enhancement. Each activity is assigned a specific number of points according to its environmental impact. Practices that provide greater ecological benefits, such as establishing biodiversity areas, earn more points, while less intensive actions receive fewer points. Farmers make their selections annually, allowing for flexibility in adapting their practices while contributing to environmental goals (European Union, 2023).

This performance-based system rewards farmers for greater environmental efforts. The more points they accumulate, the higher the financial support, encouraging them to adopt more ambitious sustainability measures. Additionally, the flexibility of this system enables farmers to customize their participation based on the needs of their land, making it suitable for both small and large farms (European Union, 2023).

7.3.3. Subsidies for Investment in Technology

Through eco-schemes, the Common Agricultural Policy (CAP) also wants to incentivise farmers to adopt Precision Agriculture techniques. In addition to these measures, several funding programs directly support investments in technology and digitalisation. Most financial support for Precision Agriculture falls under Pillar II of the European Agricultural Fund for Rural Development (EAFRD) (see Figure 120), which is co-managed by EU Member States and regions (Heyl et al., 2023). The EAFRD co-finances Precision Agriculture projects through investment grants and financial aid. Through that, farmers should receive the necessary resources to modernise operations, scale production, and integrate advanced technologies in alignment with the CAP (European Union, 2023).

One of the key funding mechanisms supporting Precision Agriculture is Measure 4 of the Rural Development Programme (RDP), which focuses on investments in physical assets. Within this framework, Sub-Measure 4.1—Support for Investments in Agricultural Holdings—provides financial support for farm modernisation, including new machinery, storage facilities, and Precision Agriculture technology (Commission, 2025). Funding rates vary by country and region. In the Netherlands, for example, the Rural Development Programme (RDP) allocated €361 million to Sub-Measure 4.1 for farm modernisation between 2014 and 2020. As of April 2020, 19.1% of this budget had been utilized (fi-compass, 2020).

Another key initiative is Measure 16, which focuses on innovation and digital farming. Under this measure, Sub-Measure 16.1 (M16.1) plays a crucial role in supporting projects within the European Innovation Partnership (EIP-AGRI). This sub-measure strongly promotes Precision Agriculture, digital tools, and advanced agricultural technologies to enhance productivity and sustainability. Many RDPs have incorporated digital farming technologies within their M16.1 projects (ENRD, 2015).

Additionally, Horizon Europe, while not part of the CAP, offers research and innovation grants for robotics, AI, and automation in agriculture. Farmers, cooperatives, and agribusinesses can participate in pilot projects to explore the potential of these technologies.

7.3.4. Subsidies Targeted at Small-Scale Farms

The EU's revised Common Agricultural Policy (CAP), introduced in January 2023, aims to redistribute support more fairly, with programs such as CRISS (additional payments for the first hectares under BISS) and the Small Farmers Payment (PSF) designed to assist small-scale farms (European Union, 2023). The PSF simplifies direct payments by merging multiple schemes, including BISS, CRISS, eco-schemes, CIS-YF, and CIS (see Figure 120). Farmers receive either a standard lump sum payment—equal for all recipients—or a payment per hectare, with a maximum of €1,250 per farm. However, recipients must still comply with Good Agricultural and Environmental Conditions (GAECs) (European Commission, 2023a).

Despite these efforts, the CAP continues to rely primarily on per-hectare payments, which may still disadvantage small-scale farms (European Union, 2023) This system is sustaining the 'get big or get out' dynamic in the agricultural sector (Al-Amin et al., 2022), as larger farms benefit disproportionately due to economies of scale - not only in subsidies but also in machinery, field labour and overall efficiency (Clough et al., 2020).

7.3.5. Perception of Subsidies

Subsidy structures and their perception by farmers were among the topics explored in the expert interviews. They revealed a deep ambivalence toward subsidies and incentives in agriculture. While financial support is generally welcomed, many farmers feel that these programs impose too many restrictions, limiting their autonomy. The growing conflict between agriculture and nature conservation authorities reflects this tension, as farmers increasingly view conservation measures as intrusions on their property rights. Regulations like eco-schemes, which come with various conditions, create a sense of external control, reinforcing reluctance to accept suggestions on how things could be done 'better,' whether from society or government agencies (Expert Interviews, 2025).

'There is a major conflict between agriculture and nature conservation. The regulations are so strict that, in practice, farmers lose control over their land. And that is the real problem.'

- Expert Fletschberger

Another concern is the 'educational' approach of many funding programs. The underlying assumption that policymakers and institutions know best how farms should be managed is met with resistance. While some measures are seen as reasonable, many farmers engage with subsidy programs primarily for financial reasons, often questioning their ecological or practical value (Expert Interviews, 2025).

Experts point to structural issues within subsidy-dependent agriculture, emphasising its long-term negative consequences. Many small-scale farms remain economically viable only due to financial aid, forcing them to comply with regulatory requirements that may not be practical or ecologically relevant. This dependency erodes farmers' autonomy and perpetuates a cycle in which agricultural decision-making is increasingly dictated by external funding conditions (Expert Interviews, 2025).

'At some point, farmers are no longer working for their products, but only for the subsidies. ... Many openly admit 'I only do it because the subsidies require it.' But these policies are ... a kind of re-education for farmers - one that does not go down well with farmers"

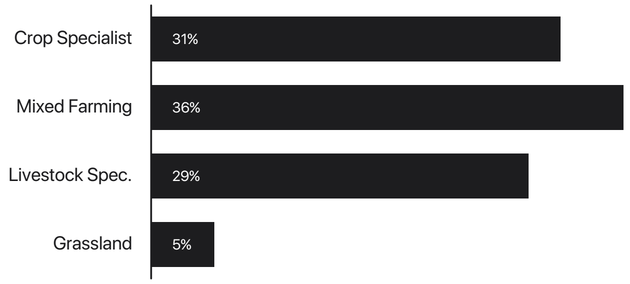
- Expert Fletschberger

7.4. Quantitative Research

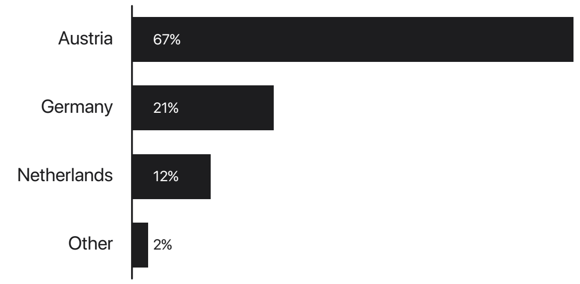
7.4.1. Sociodemographics of Participants

Data collection ran from January 1 to March 15, 2025, using a snowball sampling method. Initial interviewees shared the survey within their networks, supplemented by outreach in online farming communities (e.g., Reddit). To mitigate selection bias, participants were recruited from diverse communities and countries, ensuring a broad range of network diversity. The final sample consisted of 44 valid responses from active farmers and agricultural decision-makers, yielding a 52% response rate. Responses from non-agricultural participants and incomplete submissions were entirely removed from the dataset. While the study primarily targeted crop and mixed farms, livestock farmers were not excluded, as Pearson and Spearman correlation analyses showed no statistically significant impact of farm type on general responses. However, for crop-specific questions, such as the number of cultivated crops, responses from livestock-only farmers were excluded. Mixed farms were included in all analyses.

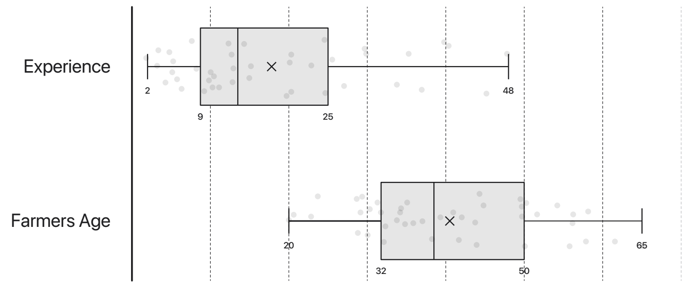
Farming Specialisation



Nationality



Experience & Age



Farmsize

Figure 122: Sociodemographics of Participants

Conflict of Interest
The author declares no conflict of interest. This thesis was conducted with support of a company. The company did not influence the results or conclusions presented in this work. All presented views reflect those of the author and involved individuals. The thesis does not claim to reflect the views of the company

Statement on AI use
This thesis benefited from the use of AI tools (e.g. ChatGPT) for language refinement, idea structuring, and feedback generation. All content and conclu¬sions are the author's own, and critical analysis was performed independently.

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